Estimating the Transmission Risk of COVID-19 in Nigeria: A Mathematical Modelling Approach

Irany FA^{1,3}, Akwafuo SE^{1,3*}, Abah T^{2,3}, Mikler AR^{1,3}

¹Department of Computer Science and Engineering, University of North Texas, USA

²College of Health and Public Service, University of North Texas, USA

³Center for Computational Epidemiology and Response Analysis (CeCERA), University of North Texas, USA

Corresponding Author: **Sampson E. Akwafuo**

Address: Department of Computer Science and Engineering, University of North Texas, USA.

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Abstract

Objectives: The potential burden of COVID-19 in sub-Saharan African might be substantially more significant than reported, and more than the existing health system can handle. Hence, in this study, we estimate and project the burden and transmission risk of COVID-19, in Nigeria, using current interventions.

Methods: Modified SEIR epidemic mathematical model was used to simulate the disease progression in weeks, for up to 19 weeks. Different situations, involving zero-intervention and varying degrees of interventions are modeled. For the intervention phase, 25% and 75% social distancing are considered, while border closure includes 80% closure of airports, seaports, and intra-state borders, using available data as of 15th May 2020.

Results: The effects of various interventions on the Ro of COVID-19 are presented. A higher percentage of social distancing appears to be more effective in controlling the spread of COVID-19 in Nigeria than border closure. Up to 131,000 persons could be infected if there are no interventions.

Conclusion: According to our results, it is easier to enforce 75% closures than 25%, as the percentage of the population complying with social distancing is higher when at least 75% of public places were closed. The minimum requirement of the population percentage that needs to comply with the social distancing advice, to weaken the epidemic can be obtained from the model.

Keywords

COVID-19, Transmission Risk

Introduction

In late 2019, coronavirus disease 2019 (COVID-19) emerged in Wuhan, Hubei province of China, causing a pandemic that has continued to wreak havoc, through unprecedented global spreading. As of April 3, 2020, at least 1,088,878 cases have been confirmed in over 180 countries, 200 territories, and five international ships, with a case fatality rate of 5.4% [1,2]. In Africa,

all but four countries have reported cases. The first case of the continent was confirmed on February 14, 2020, in Egypt. The first confirmed case in sub-Saharan Africa was in Nigeria. Most of these cases were individuals who just arrived from Europe and the United States. There are concerns about the spreading of COVID-19 in Africa. The reason is most of the healthcare systems are inadequate, having problems

such as lack of equipment, lack of funding, insufficient training of healthcare workers, and inefficient data transmission. The pandemic could also cause substantial economic issues across the countries. As of April 3, Nigeria has recorded 210 cases, with a case fatality of 1.9% [3]. The potential burden of COVID-19 in Nigeria might be substantially more significant than reported, and more than the health system can handle. In this study, we estimate the burden and transmission risk of COVID-19, using hybrid mathematical modeling.

There are still developing virologic details about the COVID-19. However, it is known to belong to the class of infections associated with humans but linked to animal origins, and this is typical of all Severe Acute Respiratory Syndrome coronaviruses (SARS-Cov). According to the International Committee on Taxonomy of Viruses [4], Coronaviruses belong to the family of *Nidovirales* and the sub-family of *Coronavirinae*, with four identified strains (*alpha coronavirus*, *beta coronavirus*, *gamma coronavirus*, and *delta coronavirus*), of which alpha and beta Coronavirus strains mostly affect the respiratory tracts of humans, with human to animal transmissions typical with the other two strains [5]. Coronavirus disease spreads primarily through contact with an infected person when they cough or sneeze. It also spreads when a person touches a surface or objects that have the virus on it and then touches their eyes, nose, or mouth. Other characteristics of the disease presentation include communal transmission. The basic reproduction number R_0 , which is generally considered low for SARS-CoV infections, however, posts higher values in COVID-19. The study in [6] identifies varying modes of transmission, including community spread, international and local travels, and some interventions (government and individual action; quarantine; restricted movements and social distancing. Others include the influence of geographic location, humidity, and temperature on the scale of the epidemic. There are questions about coronaviruses affected by these environmental factors. The study in [7] suggests high temperature and humidity may have influenced the transmission of SARS-CoV in China. The report suggests a decline in the rate of transmission of infection in relatively humid conditions and high

temperatures. Similar findings provide support to previous studies on the influence of temperature on the infection rates [8,9]. Among others, persistent dry cough, fever, nausea, and vomiting, fatigue, and pneumonia were reported to be common among patients, although at varying degrees and length of contracting the virus [10]. Some of the interventions reported as addressing or mitigating the effects of disease transmission include the establishment of a contingency system; examples include monitoring, contact tracing and identification of international travelers, early diagnosis, early isolation of infected patients, government actions (including national /city lockdown, an extension of the holiday period, hospitalization and quarantine) [11,12]. Peng used the classical susceptible, exposed, infectious, and recovered model (SEIR) to estimate the duration of the COVID-19 epidemic in multiple cities in China. Similar models have been used to study the dynamics of other viral outbreaks [13,14]. The length of infection, reproduction number, and quarantine time were the parameters used to forecast the inflection point, recession time, and the magnitude of the epidemic (depending on the commencements of intervention). The duration of the outbreak in China was estimated to last between one month to four months, affected by temperature, mitigation intensity, individual, and government actions [15].

Materials and Methods

We developed a hybrid stochastic mathematical model, with some deterministic inputs, involving a modified version of S-E-I-R epidemiological modeling structure. Modeling real-life situations allow researchers to comprehensively study an otherwise complex set of events, environment or populations and their interaction with causative agent factors. Mathematical models simulate the spread of infectious diseases within a host population. They can be used to investigate mechanisms underlying disease spread, or to predict the future trajectory of an epidemic and impacts of selected control measures. Several disease models have differing assumptions about mixing patterns between hosts. Mathematical and agent-based models have proven to be very useful in studying disease dynamics and assessing treatment strategies for specific groups and general populations [16-19].

Similar structures have been used recently in investigating the dynamics of the COVID-19 [20]. The population is divided into six groups: Susceptible (S), Exposed (E), Infected (I), Hospitalized (H), Recovered (R), and Removed (D). The Susceptible group represents all members of the public that are prone to contacting the disease, due to interactions with other population sets. The Exposed group consists of individuals who have been exposed to the virus, and their infections are in a latent stage. These individuals progress to the infectious group, with zero or more symptoms, by a relative rate κ . Infected persons can move to the hospitalized group (H), by a rate α . The number of deaths is recorded in the removed (D)

group. The relationships among the groups are presented in the model structure in **Fig-1**. The population in the model N, at time t , is equal to the sum of all groups. Model parameters and descriptions are presented in **Table-1**.

Fig-1: Model Diagram

Table-1: Model Parameters and Description

Parameter	Description	Value	Reference
β_e	Transmission rate among general population	0.864	[24]
β_H	Transmission rate from hospitalized population	0.63	[14]
$1/k$	Incubation period	5.39 days	[24]
$1/\alpha$	Infection to hospitalization period	7 days	[20]
μ	Mortality rate	0.0255	[24]
ω_1	25% Social distancing rate	0.09	Estimated
ω_2	75% Social distancing rate	0.12	Estimated
$\dot{u}$	border closure rate	0.81	Estimated
η	Natural death rate	0.014	[16]

Nigeria is used as a case study in the model. The current population of Nigeria is estimated to be 204 million [21]. The prevailing situation of COVID-19 in Nigeria as of May 15th, 2020, as released by the National Center for Disease Control [3], is used as the initial values for all model groups. Our model considered events during pre- and post-intervention scenarios, similar to the general population modeling scenarios used in [22] for the study of Ebola virus transmission. The initial scenario explores the possible behavior of viral transmission instead of public health interventions.

Parameter Estimation:

Due to the paucity of data and modeling rates, a sampling algorithm, based on Bayesian Inference, for estimating and improving model simulation accuracy

is used. Reasonable parameter estimation with uncertainty analysis is important in predictions [23]. The sampling method assumes these parameters are independent and repeatedly use the previous number of daily confirmed cases to iterate in the multidimensional space composed of all parameters and obtain optimal estimation by constructing the likelihood function. Assuming $p(\emptyset)$ represents the parameters prior distribution, then $p(\emptyset|\sigma)$ becomes the likelihood function, representing the probability of observation sets $\emptyset$ when the parameter is σ . The steps are highlighted below:

1. Select $k = 0$, as an initial parameter value, with $\emptyset(0)$ is chosen in space θ .
2. Sample parameters at $\emptyset = (k + 1)$ based on the prior uniform distribution, or normal

distribution.

3. Obtain the acceptance rate, based on the $P(\phi|\sigma(k))$, $P(\phi|\sigma(k+1))$ and prior distribution. Using the acceptance level, determine if there is a change, otherwise accept the previous value.
4. Repeat step 2 until the required number of iterations is reached.

The normal distribution probability function is:

$$p(\phi|\sigma) = \prod \prod \frac{1}{\sqrt{2\theta(\sigma)}} e^{-\frac{\varepsilon\theta}{2\theta^2(\sigma)}} \quad (1)$$

The second major scenario models outbreak transmissions and intervention impacts in the post-intervention phase. Two different interventions, social-distancing, and border-closure are further modeled. Different rates of compliance with social distancing public health advice and lockdown are used to study the transmission. The model equations are presented below:

$$\frac{dS(t)}{dt} = -\lambda S \quad (2)$$

$$\frac{dE(t)}{dt} = \lambda S - \kappa E \quad (3)$$

$$\frac{dI(t)}{dt} = \kappa E - \alpha I - \mu I \quad (4)$$

$$\frac{dH}{dt} = \alpha I - (1 - \mu)H - \mu H \quad (5)$$

$$\frac{dR(t)}{dt} = (1 - \mu)H \quad (6)$$

$$\frac{dD(t)}{dt} = \mu H + \mu I + \eta N \quad (7)$$

The force of infection λ is calculated using the following equation:

$$\lambda = \frac{(\beta_{cI} + \beta_{HH})}{N} \quad (8)$$

The susceptible group is exposed to the novel coronavirus through the infected and hospitalized group. As the susceptible group is exposed to the virus through two groups, we have considered two different types of transmission rates: a rate of transmission

among the community members and another rate for spreading the disease between the community members and the hospitalized patients. The force of infection is calculated by combining these two different transmission rates. One is the transmission rate between community members, and the other is the transmission rate between the community members and the hospitalized people. Similar transmission rates for the general population were used in the modeling study. The incubation rate (κ) is the reverse of the incubation period.

The rate of symptom onset to the hospitalization of community members (α) is calculated by reversing the period of symptom onset to hospitalization. The basic reproduction number R_0 , which is the number of secondary cases generated by infected people, for Nigeria, is considered to be 2.42 initially. [24], while the natural mortality rate is 0.014. For studying the behavior of the disease in the post-intervention phase, three different scenarios were used. 25% and 75% of social distancing interventions were applied in first and second scenarios, respectively. In this study, 25% of social distancing implies closures of worship centers and avoidance of gatherings of 50 persons and above. 75% includes closure of public transportation and all markets, in addition to the initial conditions of 25%. In the third scenario, 75% of social distancing and 80% border closure is used to study the behavior of the COVID-19 disease outbreak model in the post-intervention phase. We observed the effect of the intervention in each of these scenarios. The model parameters, description, and their values are as shown in **Table-1**. The susceptible and recovered equations after social distancing are applied as the intervention is given below:

$$\frac{dS(t)}{dt} = -\lambda S - \omega_1 S \quad (9)$$

$$\frac{dR(t)}{dt} = (1 - \mu)H + \omega_1 S \quad (10)$$

The equation for calculating the force of infection becomes:

$$\lambda = \frac{(\beta_{cI} + \beta_{HH})}{N} \omega_1 \quad (11)$$

The effect on R_0 after social distancing is applied as an intervention is given below:

$$\frac{dR_0\omega_1}{dt} = R_0\omega_1 * \omega_1 \quad (12)$$

The susceptible and recovered equations after social distancing and border closure are applied are given below:

$$\frac{dS(t)}{dt} = -\lambda S - \omega_2 S - \omega_3 S \quad (13)$$

$$\frac{dR(t)}{dt} = (1 - \mu)H + \omega_2 S + \omega_3 S \quad (14)$$

The effect on R_0 after border closure is applied as an intervention is observed using the following equation:

$$\frac{dR_0Z}{dt} = R_0Z * \omega \quad (15)$$

Results

Four different scenarios were created to aid the understanding of the outbreak dynamics in Nigeria. The first scenario corresponds to a zero-intervention

situation. Data from NCDC informs the relatively high force of infection used. As seen in **Fig-2**, the number of infected people reaches a high value within the first two weeks. In scenarios 2, 3, and 4, interventions of varying degrees were applied to the model. These are as shown in **Fig-4** and **Fig-5**, respectively. **Fig-3** compliance with social distancing increases, R_0 gradually drops. A similar effect and relationship can be seen in **Fig-4**, where a tighter restriction (75%) on public gathering and social distancing along with 80% border closure is applied. Outputs of scenario 3 are as shown in **Fig-4**. Here, the value of R_0 drops rapidly and converges to zero earlier, than in scenario 2. This is due to a higher rate of intervention used to model the outbreak in this scenario. A faster convergence of R_0 towards zero is observed in scenario 4, as shown in **Fig-4** compared to scenarios 2 and 3 (**Fig-3** and **Fig-4**). This can be attributed to the introduction of these combined interventions.

Discussions

To further understand the effects of R_0 on all levels of social distancing and border closure interventions, the relationship between the percentage of the population observing social distancing and the time

Fig-2: Number of individuals in each group with respect to time in the pre-intervention phase

Fig-3: Effects of fewer restrictions (25%) on public gathering and social distancing on R_0

Fig-4: Effects of the implementation of 75% restrictions on public gathering and 80% border closure on R_0

in weeks when the value of R_0 falls below 1 is presented in **Fig-5**. It can be seen that the percentage of the population complying with social distancing is higher when a 75% social distancing rate is used. This implies that it is easier to enforce 75% social distancing in the population. That is, individuals tend to adhere to instructions when more centers and public transportation are closed. When the rate of social distancing applied is increased, the value of R_0

falls below 1 within fewer days. In scenario 4, where 75% of social distancing is used along with 80% border closure, the time in weeks when the value of R_0 falls below 1 is the same as scenario 3, where 75% of social distancing is applied. The minimum percentage of the population that needs to comply with social distancing, to weaken the outbreak model is obtained from the model. Scenario 4 shows the effects of the application of combined intervention, to understand

the dynamics of the outbreak model. Changes in the value of R_0 for scenarios 2, 3, and 4 are shown over time in Fig-6. In all three scenarios, the value of R_0 decreases over time. It is observed that the value of R_0 for scenario 2 is larger compared to scenarios 3 and 4 at each time step time. In scenario 4, where combined

intervention is applied, the value of R_0 converges to zero earlier compared to scenario 2 and scenario 3, where single intervention is applied. It is observed that the combined intervention weakens the outbreak model earlier compared to a single intervention at a different rate.

Fig-5: Percentage of the population observing social distancing and its relationship with R_0 , when $R_0 < 1$

Fig-6: Values of R_0 over time for three different scenarios of intervention

In this paper, we present the transmission pattern, risk, and estimated burden of COVID-19 in Nigeria, using mathematical modeling. Situations of zero interventions and different degrees of interventions are modeled. For the intervention phase, 25% and 75% social distancing are considered, while border closure involves 80% closure of airports, seaports, and intra-state borders. Here, 25% of social distancing implies the closure of worship centers and avoidance of gatherings of 50 persons and above. 75% includes closure of public transportation and all markets, in addition to the initial conditions of 25%. The effects of various interventions on the R_0 of COVID-19 are presented. A higher percentage of social distancing appears to be more effective in controlling the spread of COVID-19 in Nigeria than border closure. Full compliance with social distancing is encouraged. According to our model, it is easier to enforce 75% closures than 25%, as the percentage of the population complying to social distancing is higher when a 75% rate is used. The minimum requirement of the population percentage that needs to abide by the social distancing advice, to weaken the epidemic can be obtained from the model.

Conflict of Interest

All authors have read and approved the final version of the manuscript. The authors have no conflicts of interest to declare.

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