

# System Dynamics Model for EBOLA Epidemics of West Africa: Underlying Factors & Consequence Prediction

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**Abstract**— In this paper, we model the underlying factors that cause the spread of West African Ebola virus disease (EVD) to assist in the long-term estimation of the disastrous consequences for creating future awareness. The paper works on two different system dynamics models of the epidemic based on the extended form of SIR (Susceptible, Infectious, Recovered) model. The first model reflects the number of reported cases and cumulative deaths in Guinea, Liberia and Sierra Leone using the data collected from secondary sources. The first model is validated using the CDC (Centers for Disease Control and Prevention) data, and the result is found to be a close approximation to the real data. The second model is a hypothetical model where we try to establish a relation between the control measures and the infection rate and, thus provides a better forecast for the disastrous consequences in terms of the cumulative number of populations affected by the disease. We expect this sort of models would help in the analysis of such epidemic cases in future and reduce the number of deaths by providing proper forecast considering the underlying factors.

**Index Terms**— System Dynamics, EBOLA, Epidemic, SIR Model, West Africa, Causes & Factors, Prediction

## 1 INTRODUCTION

The West African Ebola virus epidemic during the years 2014–2016 is one of the most widespread outbreaks of Ebola virus disease (EVD) in recent times which caused significant loss of life and socioeconomic disruption in the region, mainly in Guinea, Liberia, and Sierra Leone. The World Health Organization (WHO) had reported [1] a total of 28,616 suspected cases and 11,310 deaths; although the death figures don't depict the full magnitude of the outbreak. Ebola virus disease (EVD) is also known as Ebola hemorrhagic fever which is often considered as a fatal illness in humans.

EVD had first appeared in 1976 in two simultaneous outbreaks in West Africa [1, 2]. The first case was in South Sudan and the second one was in the Democratic Republic of the Congo (DRC). The latter incident occurred in a village near the Ebola River, from which the disease was named as Ebola [3]. The disease was thought to be endemic or limited to a specific population or locality before the 2014–2016 outbreak. Previous outbreaks were brought under control within a few weeks. But during the year 2014–2016, the outbreak had reached to epidemic level involving several neighboring countries and some other distant countries through secondary transmission chains. There were several causes that contributed to the failure of the outbreak: extreme poverty, dysfunctional health care systems, distrust of government after years of armed conflicts, the delay in identifying the virus, and lack of timely response [4, 5]. Other factors included local burial customs of washing the body and the unprecedented spread of Ebola to densely populated cities.

In this work, we try to identify various independent and dependent factors that contributed to the outbreak and formulate a mathematical model of the epidemic. The close system dynamics model to represent this type of epidemic is the SIR (Susceptible-Infected-Recovered) model. We have extended the basic SIR system dynamics model by considering other factors as seem important. We have used real data values of several factors such as contact rate, infectivity, the average time to show symptoms, the average time to quarantine, average incubation period, case fatality percentage, and average recovery time from the hospital, etc. Our objective in this work is to model the epidemic in such a way that it can facilitate forecasting over long-term and the model can be reused for similar sorts of analyses by changing the values of the underlying parameters.

The rest of the paper is organized as follows. Section 2 presents short statistics on EBOLA virus and our research objectives. Section 3 provides literature reviews of the similar type of modeling efforts and the additional contribution of this work. Section 4 provides our base model details such as causal-loop, and stock and flow diagram along with mathematical formulation and simulation results. Section 5 discusses our extended model. Section 6 provides a comparison of the base and the extended model. Section 7 discusses the conclusions and major findings of the study.

## 2 BACKGROUND OF THE STUDY

### 2.1 Short Statistics on Ebola Outbreak

The first case of the Ebola virus outbreak in recent times was recorded in Guinea in December 2013, and later the disease had spread to Liberia and Sierra Leone, with minor outbreaks occurring elsewhere. The disease caused a significant outbreak in

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Guinea, Sierra Leone, and Liberia than the rest of the countries in Africa. According to the WHO [1], there are 3811 reported cases and 2543 deaths in Guinea, 10675 reported cases and 4809 deaths in Liberia, and 14124 reported cases and 3956 deaths in Sierra Leone. Some other countries were also impacted by secondary transmission. Among them, 20 reported cases and 8 deaths in Nigeria, and 8 reported cases and 6 deaths in Mali. There are some other reported cases in Italy, United Kingdom, Senegal, and Spain with no reported deaths due to the Ebola virus. A summary is given in Table 1.

### 2.2 Research Questions, Goals, and Objectives

We are overwhelmed with the fatality of the EBOLA epidemic in the West African region during the years 2014-2016. We have tried to analyze the impact of the disease on the population demographics such as total population and population density. Some of the research questions that we analyze during the study are:

- How can we model a similar situation to provide a close approximation about the fatality of the disease?
- How can the model illustrate the role of control measures to keep the spread of the disease in control and to reduce the infection rate?
- How can we make the model generalized enough to be useful for similar sort of epidemics modeling scenarios in the future?

Based on those research questions, our primary goal within the scope of this paper is to:

- Develop a system dynamics model for the epidemic by considering as many underlying variables as possible.
- Finding out the effectiveness of the control measures in reducing the spread of the disease.
- Finding out the trends of reported cases and deaths and compare the results among the three countries: Guinea, Sierra Leone, and Liberia.

We validate our models by comparing the reported cases and deaths for the three countries over the two years (14 March 2014 to 14 March 2016).

### 3 LITERATURE REVIEW

Several pieces of research were done previously to model the epidemic. Ivan et al. in their paper "On a fractional order Ebola epidemic model" [6] focuses mainly on the classical and fractional aspect of the SEIR models of the epidemic and are more concerned regarding the cumulative infected, exposed and recovered population. They provide a simulation for the first 300 days for the infected population and 700 days simulation for the cumulative infected population to estimate some forecasts. Rivers et al. in their paper "Modeling the impact of interventions on an epidemic of Ebola in Sierra Leone and Liberia" [7] propose a mathematical modeling of the Ebola epidemic using statistical analysis. The authors provide the simulation of estimated infected population for first 250 days for Liberia and Sierra Leone.

Meltzer et al. in their paper on "Estimating the future number of cases in the Ebola epidemic—Liberia and Sierra Leone, 2014–2015", [8] shade some insights on the cumulative number of cases and number of beds in use for a simulation duration of 6 months starting from 26 March 2014 to 26 September 2014. Although most of the above models were very helpful at the time of the crisis for forecasting reason and understanding the severity of the epidemics, the models lack to provide a long-term forecast which is necessary for taking appropriate control measures. Abdulrahman et al. [9] present a deterministic model for controlling the spread of the Ebola virus disease considering the case of Nigeria. They identify and focus only on limited control parameters which are improved personal hygiene of the susceptible population and quarantining of the infected individuals. This one seems a limited approach because there are lots of other control measures that helped to control the spread of the outbreak.

Transmission dynamics of Ebola virus are discussed in [10, 11]. The authors provided a comparative review of mathematical models of the spread and control of Ebola in the context of the recent outbreaks and showed that mathematical models offer useful insight into the assessment of the impact on publi

TABLE 1.  
 COUNTRY-WISE EBOLA VIRUS DISEASE OUTBREAKS DURING 2014-2016

Country	Year	Total Population [12] (M = Million)	Population Density (people/sq. KM) [13]	Reported Cases [1]	Reported Deaths [1]	Case fatality rate (%) [1]
Liberia	2014-2016	4.6 M	47	10675	4809	45
Sierra Leone	2014-2016	7.4 M	102	14124	3956	28
Guinea	2014-2016	12 M	50	3811	2543	67
DRC	2014	79.3 M	35	66	49	74
Nigeria	2014	176.46 M	204	0	8	40
Mali	2014	16.96 M	15	8	6	75
Senegal	2014	14.67 M	78	1	0	0

health measures. Lewnard et al. [14] present a transmission model of Ebola virus by considering the reported EVD cases and deaths in Montserrado county of Liberia. Their study focuses on the assessment of the effectiveness of expanding EVD treatment centers and allocating protective kits for controlling the outbreak, but the model is limited to the specific county population data. Christian Althaus [15] provides an estimate of the reproduction number of Ebola virus during the 2014 outbreak in West Africa, but the model simulation output is only until September 01, 2014, where the disease continued its impact till the first quarter of 2016. In our study, we are presenting a long duration estimates which consider the control measures into the effectiveness of the model. We provide here the cumulative number of deaths and reported cases for around 800 days to validate the model because these data are available from CDC and which also gives us a good insight regarding the EBOLA epidemics magnitude of severity. While the other research papers do not establish any relationship of the control measures in reducing the infectivity, deaths and reported cases, which we try to depict in our system dynamics models.

#### 4 SYSTEM DYNAMICS BASIC MODEL

In this section, we discuss the causal-loop diagram, stock and flow diagram, and the underlying parameters and equations for the basic system dynamics model. We shall also present the simulation results and validate our simulation output using CDC data.

##### 4.1 Causal Loop Diagram

Fig. 1 shows the causal loop diagram for the basic model. The model is an extended form of common SIR model. Here the

susceptible population gets infected and transfer to the asymptomatic population (who are infected but not shown the symptoms yet). Then the asymptomatic population transfers to the symptomatic population. There are two branches getting out from the symptomatic population: one is to deaths through the symptomatic death rate and other is the quarantined population through the quarantined rate. The quarantined population again either branches to death population or recovered population. In the base model, control measure assists the symptomatic people to safeguard from the disease. Control measures assist people leaving the quarantine per day, means the more effective control measure the more people can be safeguarded timely and more people can leave out of the incubation period. Control measure also has a feedback loop towards cases, which means it can control the number of cases. Case fatality percentage contributes to the case fatality rate. Case Threshold is being used to balance the deaths population after a certain number of cases has been reported.

##### 4.2 Stock AND Flow Diagram

The stock and flow diagram of the basic model is presented in Fig. 2. Again, the same independent and dependent variables are used to draw the stock and flow diagram. We have used Vensim software for drawing and simulating the model.

##### 4.3 Input Data

The basic system dynamics model is generatized model which is applicable to all three countries. There is no difference among the variables of the models in the three different countries situations, but they differ only in the value. Table 2 presents the data that we have used for the three different countries' system dynamics model. Data have collected from secondary sources [5-8, 16, 17].

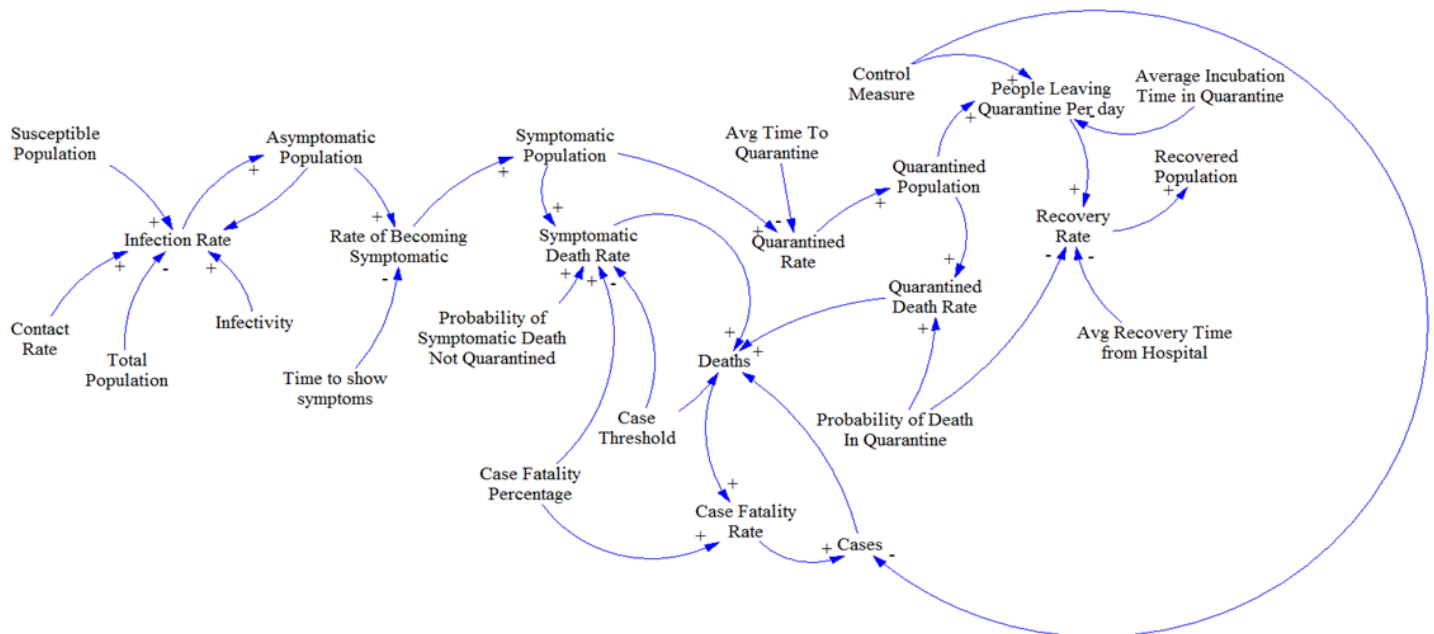


Fig. 1. Causal loop diagram of the basic system dynamics model.

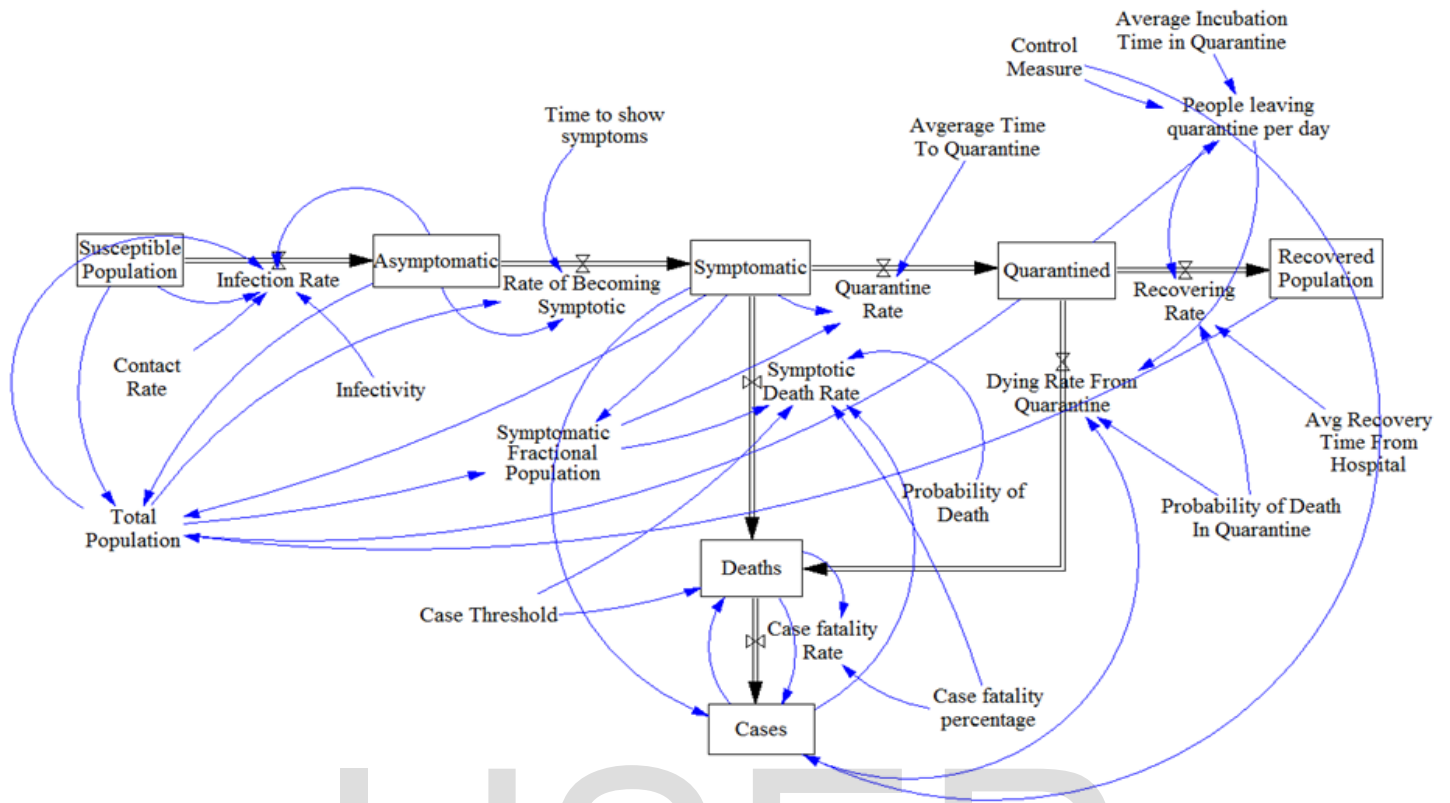


Fig. 2. Stock and flow diagram of the basic model of Ebola epidemic.

TABLE 2.  
 PARAMETERS VALUES FOR THE BASIC SYSTEM DYNAMICS MODELS

Parameters	Guinea	Liberia	Sierra Leone
Contact Rate	6	7.5	7
Infectivity	0.0702	0.0702	0.0702
Time to Show Symptoms	4.5	6	6
Initial Susceptible Population	12 M	4.6 M	7.3 M
Case Threshold	2500	3000	3000
Case Fatality Percentage	0.75	0.75	0.65
Average Time to Quarantine	2	2	2
Probability of Death	0.10	0.12	0.15
Control Measure (Tuned)	1.125	2.5	1.5
Average Recovery Time from Quarantine	7	7	7
Probability of Death in Quarantine (Tuned)	0.045	0.035	0.05
Average Recovery Time from Hospital	13.5	13.5	15.5

TABLE 3.  
 INDEPENDENT INPUT VARIABLES AND VALUES FOR BASIC SD MODEL

Variable Name	Notation	Value
Contact Rate	$c$	6 contacts/day
Infectivity	$i$	0.0702
Time to Show Symptoms	$t_{symp}$	4.5-6 days
Case Fatality Percentage	$CFP$	0.65-0.75
Probability of Death	$P_d$	0.1-0.15
Control Measure	CM	0-5 (Likert scale)
Average Time to Quarantine	$t_q$	2 days
Average Incubation Time in Quarantine	$t_{iq}$	7 days
Probability of Death in Quarantine	$P_{qd}$	0.01-0.05
Average Recovery Time from Hospital	$t_{rh}$	12-15.5 days

TABLE 4.  
 VARIABLE NOTATIONS USED FOR THE SD MODEL

Variable Name	Symbolic Notation	Variable Name	Symbolic Notation
Susceptible Population	$P_S$	Symptomatic Death Rate	$R_{D_{symp}}$
Total Population	$N$	Quarantined Population	$P_Q$
Asymptomatic Population	$P_{asymp}$	Initial Quarantined Population	$P_{Q_0}$
Infection Rate	$R_I$	Dying Rate from quarantine	$R_{D_Q}$
Rate to become Symptomatic	$R_{sym}$	Recovering Rate	$R_R$
Symptomatic Population	$P_{symp}$	Death Population	$P_D$
Initial Symptomatic Population	$P_{symp_0}$	Initial Death Population	$P_{D_0}$
Quarantine Rate	$R_Q$	People leaving quarantine per day	$P_{lqd}$
Symptomatic Fractional Population	$PFR_{symp}$	Number of Reported Cases	$N_{RC}$

#### 4.4 Model Equations

The necessary model equations for the basic system dynamics model is presented below, the notations are elaborated in Table 4.

$$\text{Susceptible Population, } P_S = P_{S_0} + \int -R_I \tag{1}$$

$$\text{Total Population, } N = P_S + P_{asymp} + P_{symp} + P_Q + P_R \tag{2}$$

$$\text{Infection Rate, } R_I = \frac{P_S * c * i * P_{asymp}}{N} \tag{3}$$

$$R_{sym} = \frac{\text{Asymptomatic Population}}{\text{Total Population} * \text{Time to show symptoms}} = \frac{P_{asymp}}{N * t_{symp}} \tag{4}$$

$$P_{symp} = P_{symp_0} + \int (R_{sym} - R_Q - R_{D_{symp}}) \tag{5}$$

$$PFR_{symp} = \frac{\text{Symptomatic Population}}{\text{Total Population}} = \frac{P_{symp}}{N} \tag{6}$$

$$R_{D_{symp}} = \text{If Then Else (Cases} \leq \text{Case Threshold, } CFP * P_d * PFR_{symp}, 0) \tag{7}$$

$$R_Q = \frac{(1 - \text{Symptomatic Fractional Population}) * \text{Symptomatic}}{\text{Average Time To Quarantine}} = \frac{(1 - PFR_{symp}) * P_{symp}}{t_q} \tag{8}$$

$$P_Q = P_{Q_0} + \int (R_Q - R_{D_Q} - R_R) \tag{9}$$

$$P_D = P_{D_0} + \int (\text{If Then Else}(\text{cases} \leq \text{Case Threshold, } (R_{D_Q} + R_{D_{symp}}), -0.012) \tag{10}$$

$$N_{RC} = N_{RC_0} + \int (\frac{CFR * P_D * P_{symp}}{CM}), \text{ where } N_{RC_0} = 1 \text{ assumed} \tag{11}$$

$$P_{lqd} = \frac{\text{Control Measure} * \text{Quarantined Population}}{\text{Average Incubation Time in Quarantine}} = \frac{CM * P_Q}{t_{iq}} \tag{12}$$

$$R_{D_Q} = \text{People Leaving Quarantine per day} * \text{Probability of Death in Quarantine} = P_{lqd} * P_{qd} \tag{13}$$

$$R_R = \frac{(1 - \text{Probabilit of Death in Quarantine}) * \text{People Levaing Quarantine Per day}}{\text{Average Recovery Time From Hospital}} = \frac{(1 - P_{qd}) * P_{lqd}}{t_{rh}} \tag{14}$$

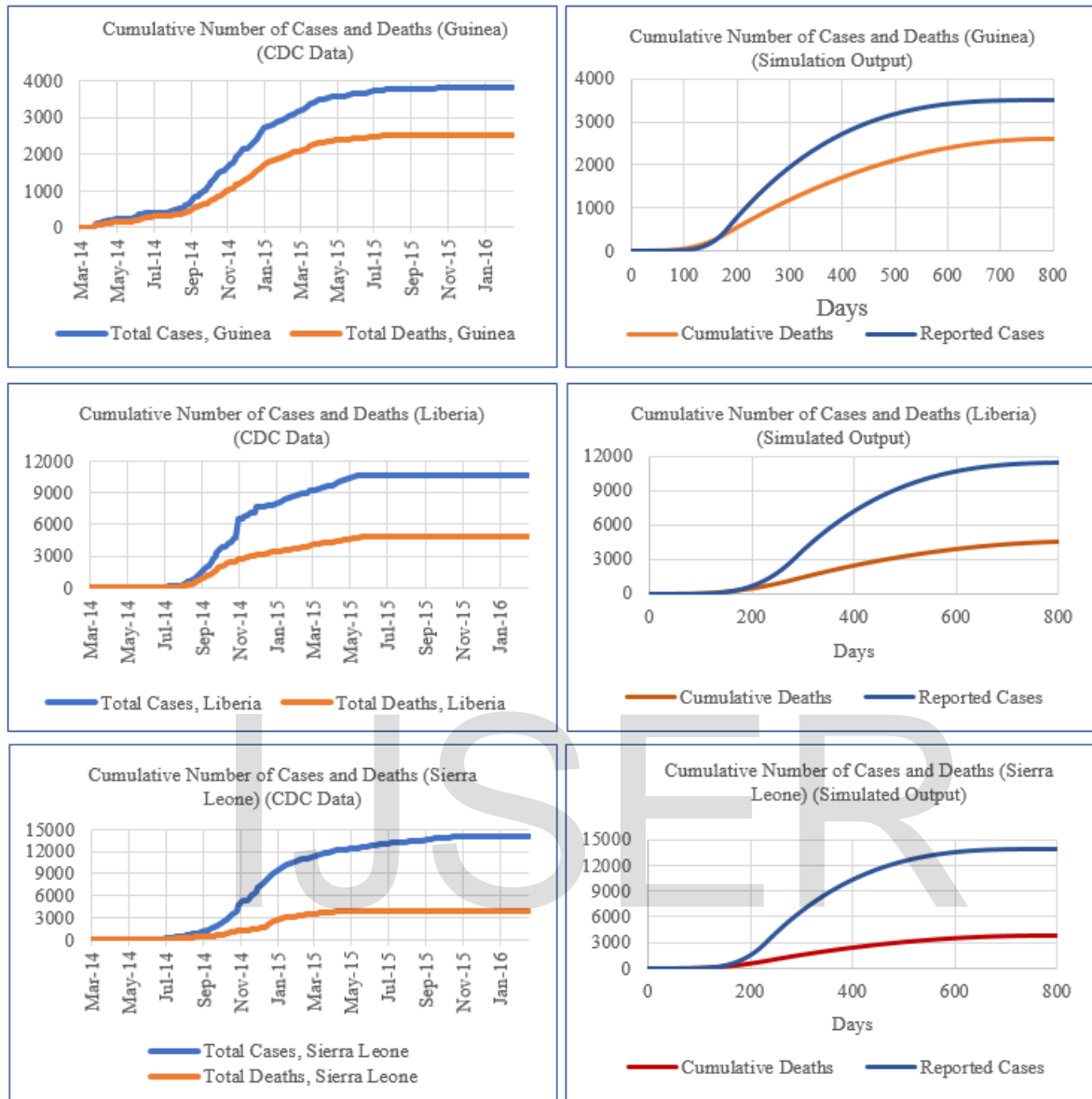


Fig. 3. The Basic SD model validation with CDC Data [18-21] for the three countries: Guinea, Liberia, and Sierra Leone.

#### 4.5 Simulation Results

Right hand side of Fig. 3 shows the simulation output for the basic model for Guinea, Liberia, and Sierra Leone. Left hand side of Fig. 3 shows the CDC data [18-21] for validating the basic system dynamics model of Ebola epidemics. As can be seen, the number of cumulative deaths for Guinea is nearly 2,500 and reported cases is nearly 3,500 after 800 days which are very close to the real data of 2,536 and 3,804 respectively. In the case of Liberia, the number of cumulative deaths is nearly 4,500 and reported cases is nearly 11,000 after 800 days which are close to the real CDC data of 4,806 and 10,666 respectively. In the case of Sierra Leone, the number of cumulative deaths is nearly 3,900 and reported cases is nearly 14,000 after 800 days which are again close to the CDC data of 3,955 and 14,122 respectively.

Almost all the simulation outputs are matched with the original data with a slight deviation in the values. Most importantly the shapes of the curves are almost identical for all the three countries simulation for both reported cases and cumulative deaths. Thus, the basic models are validated against real data from CDC. Here we take the reported cases and death figures to only for the purpose of the validation of the model because these data are readily available from CDC.

#### 5. EXTENDED SYSTEM DYNAMICS MODEL

The basic model considers the effect of control measures on balancing the number of cases and deaths while the extended model considers the effect of control measures on the infection rate on top of the basic model.

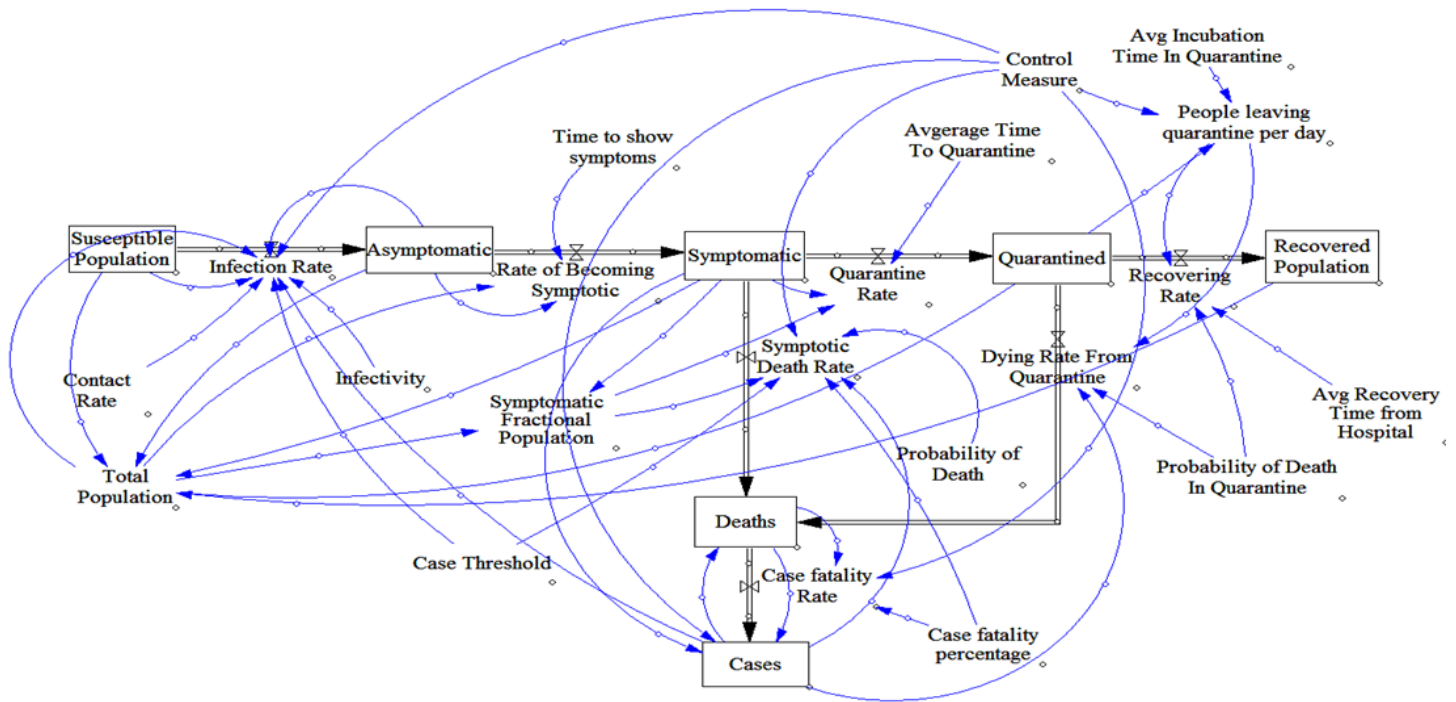


Fig. 4. Stock and flow diagram of the extended model of Ebola virus epidemics.

TABLE 5.  
 ADDITIONAL PARAMETERS' VALUES FOR THE EXTENDED MODEL

Parameters	Guinea	Liberia	Sierra Leone
Control Measure (Tuned)	3.5	3.5	5
Average Recovery Time from Quarantine	5	5	5
Probability of Death in Quarantine (Tuned)	0.01	0.025	0.025
Average Recovery Time from Hospital	12	12	14

### 5.1 Stock and Flow Diagram for Extended Model

The extended model considers the effect of control measures on the infection rate. We know that some of the infections had spread due to the unsafe burial of the deaths caused by the Ebola virus. This transmission has a significant impact on the quick spread of the disease. That is why we consider the control measures which is mainly an indication of the following of the safe burial procedures by the people who buried the deaths. In other terms, this control measures increase the situational awareness among the people and thus, contributed to reduce the infection rate. The causal loop diagram of the extended SD model is omitted because of space constraint. Stock and flow diagram are presented in Fig. 4. Input data that are different from the basic model are provided in Table 5.

### 5.2 Simulation Results of Extended Model

Simulation Outputs for the extended models of the three countries are given in Fig. 5. As can be seen from Fig. 5, the control measure help reduces the number of cumulative deaths by reducing the infection rate to some extent because the cumulative deaths have dropped below 2000 which around 2500 earlier

in the base model of Guinea case. Another thing to note is that this time the reported cases have increased. The point here is that even with a greater number of reported cases, the total number of deaths remain less than the base model. The same relation that even if the reported cases numbers have been increased in both cases in the extended model, the cumulative deaths number is reduced than that of base model for the two other countries. Validation is not possible for the extended models because there is no such data available.

### 6. COMPARISON OF BASIC AND EXTEND SD MODELS

In this section, we present the comparison of the simulation results of the basic model and the extended model. In Fig. 6, the dotted curves represent the extended model and solid curves represent the base model. One of the main objectives to extend the models is to see the effect of control measures on the infection rate. From Fig. 6 it is found that in the extended model there are more reported cases (hypothetical) but it has also reduced number of cumulative deaths (hypothetical).

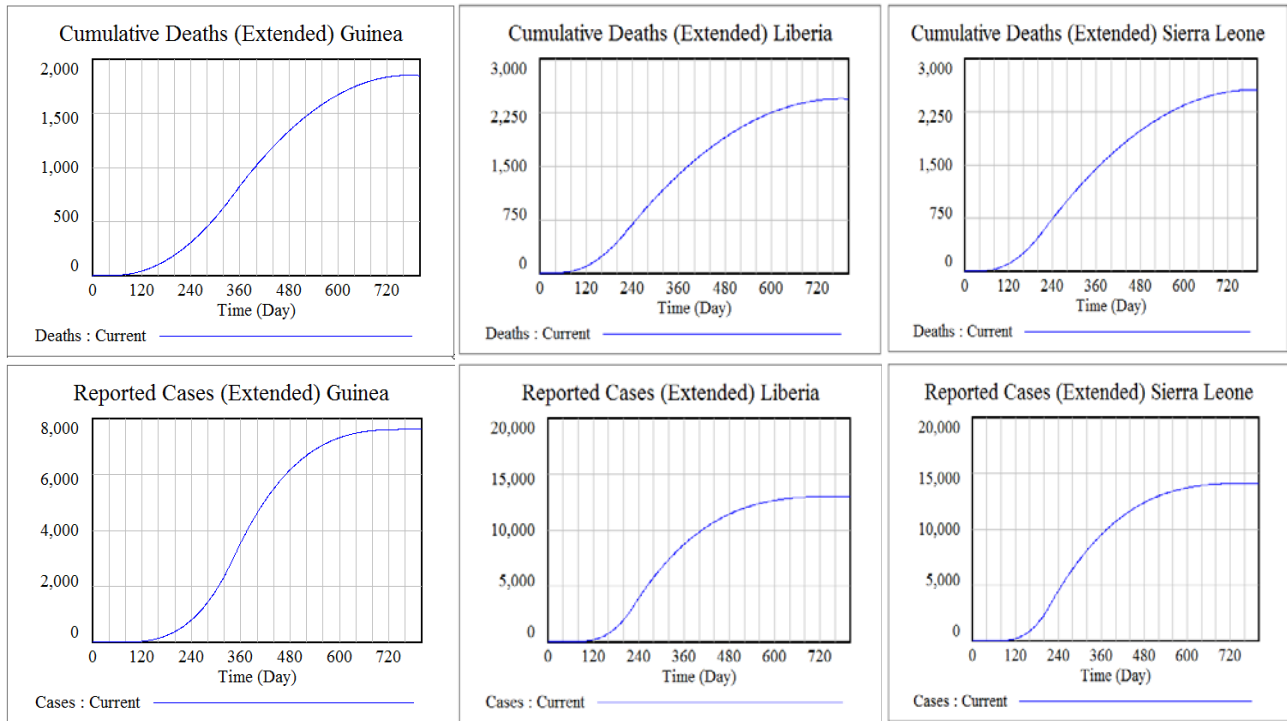


Fig. 5. Simulation output using the Extended SD models for three countries: Guinea, Liberia, and Sierra Leone.

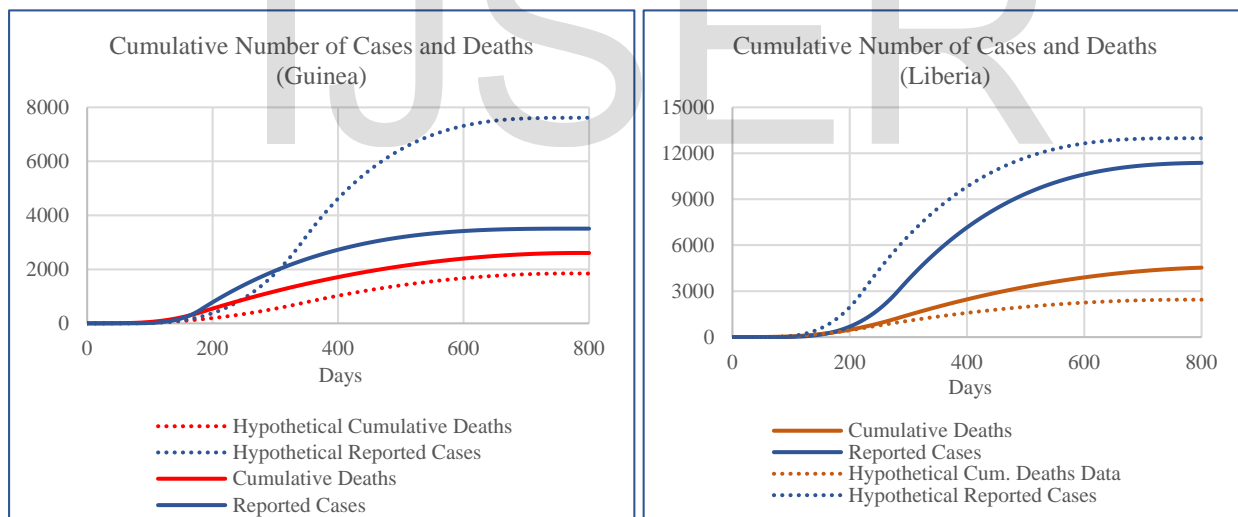


Fig. 6. Comparison of simulation output of reported cases and cumulative deaths using the Basic and Extended SD models for Guinea, and Liberia.

This means control measures can have a positive effect in reducing the deaths number by controlling the infection rate. We present the comparison for Guinea and Liberia here, but the case of Sierra Leone is having the same result.

### 7 CONCLUSIONS

Ebola virus epidemic in the West African countries during 2014-2016 was a major concern by the respective governments and international organizations who closely worked in this

field. Modeling the epidemics using system dynamics approach finds out the nature and magnitude of the disease in a time-varying manner. In our models, we try to model the underlying factors that can cause the epidemics and by taking control measures, we can reduce the loss of precious lives. Model parameters are extracted from different secondary sources. The base model simulation output is a close approximation to the real data provided by CDC. The hypothetical extend SD models capture the control measures and its impact on reducing the



number of deaths and infection rates. Various analyses from the different point of views are presented with the help of simulation from the system dynamics models. The models fulfill the research objectives and outcomes both in terms of simulation and validation perspectives. Most importantly, it shows a comparison between the outputs of the base model and the extended model. According to our knowledge, these sorts of models can be reused for similar sort of epidemic cases in future and can assist the researchers working in this field to take control measures according to the severity of the epidemics.

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