

Predict new cases of the coronavirus 19; in Michigan, U.S.A. or other countries using Crow-AMSAA method



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ABSTRACT

Statistical predictions are useful to predict events based on statistical models. The data is useful to determine outcomes based on inputs and calculations. The Crow-AMSAA method will be explored to predict new cases of Coronavirus 19 (COVID19). This method is currently used within engineering reliability design to predict failures and evaluate the reliability growth. The author intents to use this model to predict the COVID19 cases by using daily reported data from Michigan, New York City, U.S.A and other countries.

The piece wise Crow-AMSAA (CA) model fits the data very well for the infected cases and deaths at different phases during the start of the COVID19 outbreak. The slope β of the Crow-AMSAA line indicates the speed of the transmission or death rate. The traditional epidemiological model is based on the exponential distribution, but the Crow-AMSAA is the Non Homogeneous Poisson Process (NHPP) which can be used to modeling the complex problem like COVID19, especially when the various mitigation strategies such as social distance, isolation and locking down were implemented by the government at different places.

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1. Introduction

It was announced by the “WHO” that COVID19 was first localized in Wuhan, Hubei Province, China in December 2019, and it has been a significant human threat to the public health around the globe.

As of June 26, 2020: globally, there have been about 9.9 million confirmed case, and about 498,733 reported deaths ([WorldOMeters](#)). In U.S.A., there are about 2,573,730 confirm cases, and about 127,845 reported deaths ([WorldOMeters](#)). In the state of Michigan, there are about 69,329 confirmed cases and about 6,134 reported death at the time author writing this paper ([WorldOMeters; Click On Detroit News, 2020](#)). The COVID19 is affecting 213 countries and territories around the world and 2 international conveyances. The COVID19 is spreading into all the 50 states, District of Columbia and its territories in United States. Because of the contagious of this disease, most of the states such as Michigan have issued the staying home order to reduce the infectious speed.

The author is curious if there is a statistical model to predict this event. Since the Crow-AMSAA model is used for automotive warranty data to accurately predict the failures numbers in the field then can the model be used for predicting aspects of the effects of COVID19.

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The model was trialed to make predictions of the Michigan infected cases and deaths ([Click On Detroit News, 2020](#)) since March 16th. When the COVID19 infection data and death data were used in the model for Michigan, the model yielded a good estimation. Update models using the daily reported data from Michigan, continued to yield promising results. On March 28, 2020, the model was used for the U.S.A infected and death data ([WorldOMeters](#)) and the results supported that the Crow-AMSA model accurately predicted the USA reported data.

The Crow-AMSA model appears to be useful to predict the infected cases and deaths for a pandemic like COVID19.

The daily reported data from New York City ([New York City Gov](#)), Spain, Italy, France, Germany, UK, China and South Korea ([WorldOMeters](#)) have also been analyzed by using the piece wise Crow-AMSA model. The comparison of the speed of the transmission and death rates at different places and countries are also summarized in this paper.

2. Review of epidemiological model

There are existing epidemiological models used in the pandemic prediction.

2.1. Exponential model

It is believed that most epidemics grow approximately exponentially during the initial phase of an epidemic. $I(t)$ is the number of “diagnosed infected” case, t is the time which is measured in days ([Ranjan, 2020](#)).

$$I(t) = I_0 e^{rt} \quad (1)$$

$$\frac{dI(t)}{dt} = rI(t) = rI_0 e^{rt} \quad (2)$$

Where r is the growth rate, I_0 is the constant which can be calculated by fitting the data.

The author has trialed to use the exponential model to predict the infected cases and death based on the parameters ($y = 39.64 * \exp(0.1887 * x)$) from ([Ranjan, 2020](#)), it was working at some points at the initial of the spreading, but the exponential model does not work for the long term predictions after the initial phase of the pandemic.

2.2. Susceptible-infectious-recovered (SIR) model

SIR models are compartmental models used to simplify the mathematical modeling of infectious disease.

$$\frac{dS(t)}{dt} = -\frac{\beta}{N} S(t) I(t) \quad (3)$$

$$\frac{dI(t)}{dt} = \beta S(t) I(t) - \gamma I(t) \quad (4)$$

$$\frac{dR(t)}{dt} = \gamma I(t) \quad (5)$$

Where $S(t)$ is the number of susceptible individuals, $I(t)$ is the number of infectious individuals, and $R(t)$ is the number of recovered individuals; β is the transmission rate per infectious individual, and γ is the recovery rate, N is the population, $N = S(t) + I(t) + R(t)$ ([Ma, 2020](#)).

The basic reproduction number is given as:

$$R_0 = \frac{\beta}{\gamma} \left(1 - \frac{I_0}{N} \right) \quad (6)$$

The SIR models have been used by Ranjan ([Ranjan, 2020](#)), Canabarro, etc. ([Canabarro et al., 2020](#)) and Liu, etc ([Liu, Magal, & Webb, 2020](#)) to make the predictions. These models may involve a large number of parameters and assumptions and are therefore vulnerable to the perturbation parameters and previous assumptions, do not evaluate the goodness of the fit of the observed data and may lead to a wider prediction interval ([Wang, Xie, Wang, & Zeng, 2020](#)).

2.3. Logistic Model003A

Logistic model was developed by Belgian mathematician Pierre Verhulst (1838). Logistic model is the model which shows initially exponential growth followed a gradual slowing down and a saturation ([Ma, 2020](#)).

$$\frac{dC(t)}{dt} = rC(t) \left(1 - \frac{C(t)}{K}\right) \quad (7)$$

$$C(t) = \frac{KC_0}{C_0 + (K - C_0)e^{-rt}} \quad (8)$$

Where $C(t)$ is the cumulative total numbers of infectious, r is the exponential growth rate, K is the upper limit of population growth and it is called carrying capacity. C_0 is the $C(t)$ when $t = 0$.

The author has also trialed the logistic model for China and U.S.A data, the conclusion is that the logistic model can not be used to predict the infected numbers and deaths in whole period.

3. Crow-AMSA model

3.1. Introduction of Crow-AMSA

James T. Duane at GE Motors Division conducted the reliability growth analysis by observing the cumulative failure rates of the product subsystems during the development test. He plotted the cumulative failures versus the development time on a log-log paper (Duane, 1964). The AMSA model, a major improvement in Duane's approach was developed by Dr. Larry Crow in 1974 while he was at the Army Material Systems Analysis Activity (AMSA). Dr. Crow proposed that the Duane model can be represented as non-homogeneous Poisson process (NHPP) model under Weibull intensity function (Abernethy, 2006; Tananko, 2020).

The total confirmed infected cases or deaths $N(t)$ can be expressed as following when Crow-AMSA model applies

$$N(t) = \lambda t^\beta \quad (9)$$

Where t is the time which measured in days, λ and β are constants, they will be explained later.

The logarithm of cumulative events $N(t)$ versus logarithm time t , which measured in days is a linear plot. By taking the natural logarithms of equation (9)

$$\ln N(t) = \ln(\lambda) + \beta \ln(t) \quad (10)$$

The model intensity function

$$\rho(t) = \frac{dN(t)}{dt} = \lambda \beta t^{\beta-1} \quad (11)$$

The cumulative event rate is to use equation (9) divided by t . it is

$$C(t) = \lambda t^{\beta-1} \quad (12)$$

The intensity function is the derivative of the cumulative events $N(t) = \lambda t^\beta$, $\rho(t)$ is called the rate of occurrence (ROC). In equation (10), the scale parameter, λ , is the intercept on the y axis of $N(t)$ when $t = 1$, ($\ln(1) = 0$); the slope β , is interpreted in a similar manner as a Weibull plot, If the slope β is greater than 1, the transmission rate is increasing, the transmission rate is more rapid, if the slope β is smaller than 1, the transmission rate is decreasing, the transmission rate is slower, if the slope β is equal to 1, the process is named the Homogenous Poisson Process (HPP), if the slope β is not equal 1, the process is called Non Homogenous Poisson Process (NHPP).

Weibull distribution is invented by Dr. Waloddi Weibull in 1937, it is widely used by engineering reliability field for the failure data analysis. The slope of the Weibull plot β indicates which class of failures is present. CA model is also called as "Weibull Power Process" (WPP). The interpretation of the slope β is similar to Weibull analysis. However, the individual time to failure is used in Weibull, but the cumulative times is used in CA. Weibull distribution handles one failure mode at a time, but CA handles mixtures of situation.

3.2. The piece-wise Crow-AMSA

The piece-wise Crow-AMSA is applied to each segment of the data. Assume the point C_i ($i = 1, \dots, k-1$) (in days), k is the number of segments, the piece-wise Crow-AMSA will be:

$$\begin{aligned}
N_1(t) &= \lambda_1 t^{\beta_1} \quad (t \leq C_1) \\
N_2(t) &= \lambda_2 t^{\beta_2} \quad (C_1 < t \leq C_2) \\
&\dots \\
N_{k-1}(t) &= \lambda_{k-1} t^{\beta_{k-1}} \quad (C_{k-2} < t \leq C_{k-1}) \\
N_k(t) &= \lambda_k t^{\beta_k} \quad (C_{k-1} < t)
\end{aligned} \tag{13}$$

The two curves intercept at time C_i .

$$N_i(C_i) = N_{i+1}(C_i) \tag{14}$$

and the model parameters has the relationship

$$\lambda_{i+1} = \lambda_i C_i^{\beta_i - \beta_{i+1}} \tag{15}$$

For a system starts from time 0, and has one change point C , the log likelihood function is as following (Guo et al., 2010):

$$\begin{aligned}
L = N \ln(\lambda_1) + N_1 \ln(\beta_1) + N_2 \ln(\beta_2) + N_2 (\beta_1 - \beta_2) \ln(C) + (\beta_1 - 1) \sum_{i=1}^{N_1} \ln(t_i) + (\beta_2 - 1) \sum_{i=N_1+1}^N \ln(t_i) \\
- \lambda_1 C^{\beta_1 - \beta_2} T^{\beta_2}
\end{aligned} \tag{16}$$

The solution for the model parameters are:

$$\lambda_1 = \frac{N}{C^{\beta_1 - \beta_2} T^{\beta_2}} \tag{17}$$

$$\beta_1 = \frac{N_1}{N_1 \ln(C) - \sum_{i=1}^{N_1} \ln(t_i)} \tag{18}$$

$$\beta_2 = \frac{N_2}{N \ln(T) - \sum_{i=N_1+1}^N \ln(t_i) - N_1 \ln(C)} \tag{19}$$

where N is the total number of infected cases or deaths. N_1 is the number of infected cases or deaths in segment 1, N_2 is the number of infected cases or deaths in segment 2. T is the end time in days.

A heuristic method is needed solve the C_i iteratively (Guo et al., 2010). 1.) Plot the infected cases or death vs. time (days) in Crow-AMSAA logarithm scale. 2.) From the plot, identify the range for C_i , denoted as $[C_{i_min}, C_{i_max}]$. 3.) Set $C_{ij} = C_{i_min} + j \Delta C_i$, calculate the MLE solution for $\hat{\lambda}_i, \hat{\beta}_i, \hat{\beta}_{i+1}$ using C_{ij} . 4.) Calculate the log likelihood value using $\hat{\lambda}_i, \hat{\beta}_i, \hat{\beta}_{i+1}$, 5.) Set $j = j + 1$ and repeat step 3 and 4 until C_i reach C_{i_max} . The solution of $\hat{\lambda}_i, \hat{\beta}_i, \hat{\beta}_{i+1}$ and the value of C_{ij} that provide the largest likelihood value will be the ML solution.

3.3. The fitting methods

There are three possible methods to fit the line, the regressions, IEC (International Electrotechnical Commission) unbiased, and IEC MLE (Maximum Likelihood Estimation). The regression solution is not as accurate as the newer IEC unbiased and MLE methods except for very small sample sizes. IEC MLE solutions for interval or grouped data method is from IEC 61164 (IEC 61164 Ed. 2.0 en, 2004) (Abernethy, 2006) which describes as following:

The maximum likelihood finds the value β and λ which maximum the log likelihood function. The method differentiates the logarithm of the likelihood function with respect the β and λ , equals the resulting expression to zero, and simultaneously solves for β and λ .

Grouped or interval data is gathered by inspection at intervals or with coarse data collection, i.e. daily or monthly reports. The intervals do not have to be equal in time or number of events. A more complex maximum likelihood equation is needed to estimate the shape parameter β for grouped or interval data.

$$\sum_{i=1}^K n_i \left[\frac{t_i^\beta \ln(t_i) - t_{i-1}^\beta \ln(t_{i-1})}{t_i^\beta - t_{i-1}^\beta} - \ln(t_k) \right] = 0 \tag{20}$$

Where K is the number of intervals, n_i is the number of cases at i th interval or event, t_i is the cumulative time (days) at i^{th} interval or event. t_K is the cumulative total time (days). β is the approximate value of β which the Crow-AMSAA slope. An iterative method is needed to solve the MLE β .

Calculate an MLE estimate of λ which the Crow-AMSAA scale parameter.

$$\lambda \hat{=} \frac{\sum_{i=1}^K n_i}{t_K^\beta} \quad (21)$$

The instantaneous MLE intensity function is similar to (11)

$$\rho(\hat{t}) = \lambda \hat{\beta} t^{\hat{\beta}-1} \quad (22)$$

Using IEC 61164 methods, the Cramer-Von Mises statistic accepts the goodness of fit at a Fit-p% of 10% as indicated on the plot.

3.4. The prediction

The short term (1–2 days) infected cases or deaths can be predicted by plugging the cumulative time (days) to the last piece-wise CA model where β_k and λ_k have been calculated by using the previous data. Since the determination of change point C of piece-wise CA is based on the data, the change point C is depending on the situation and characters of the spreading and deaths at that period. If we attempt to predict longer term of infected cases or death, the duration (or change point C) of the future piece-wise CAs has to be assumed based on previous piece-wise CA, the effectiveness of government policy and other factors. The examples will be shown in Figs. 4, 7 and 10.

4. Crow-AMSAA data analysis

In China: The daily confirmed COVID19 cases and deaths in China are reported in the website in the reference ([WorldOMeters](#)). The Crow-AMSAA model [equation (10) $\ln L_n$ to $\ln L_0$] is applied for the cumulative total confirmed cases in China [Fig. 3]. The time period is from 1/22/2020 to 4/11/2020. It is obvious the piece-wise Crow-AMSAA can be used to fit the data. It is very interesting to see there are three phases for the COVID 19 infection. The first phase (1/22/2020 to 2/11/2020) is the growth stage where CA slope β is $1.683 > 1$, and the infectious rate is increasing. The CA slope β of the second phase (2/12/2020 to 2/21/2020) is $0.731 < 1$, and the infectious rate is decreasing. The third phase (2/22/2020 to 4/9/2020) is toward the saturation stage where CA slope β is $0.068 < 0.731$ (second phase slope β) < 1 . Chinese government locked down Hubei, Wuhan on 1/22/2020, the 14 days' isolation of the individuals who had the contact with the COVID19 infected people, staying

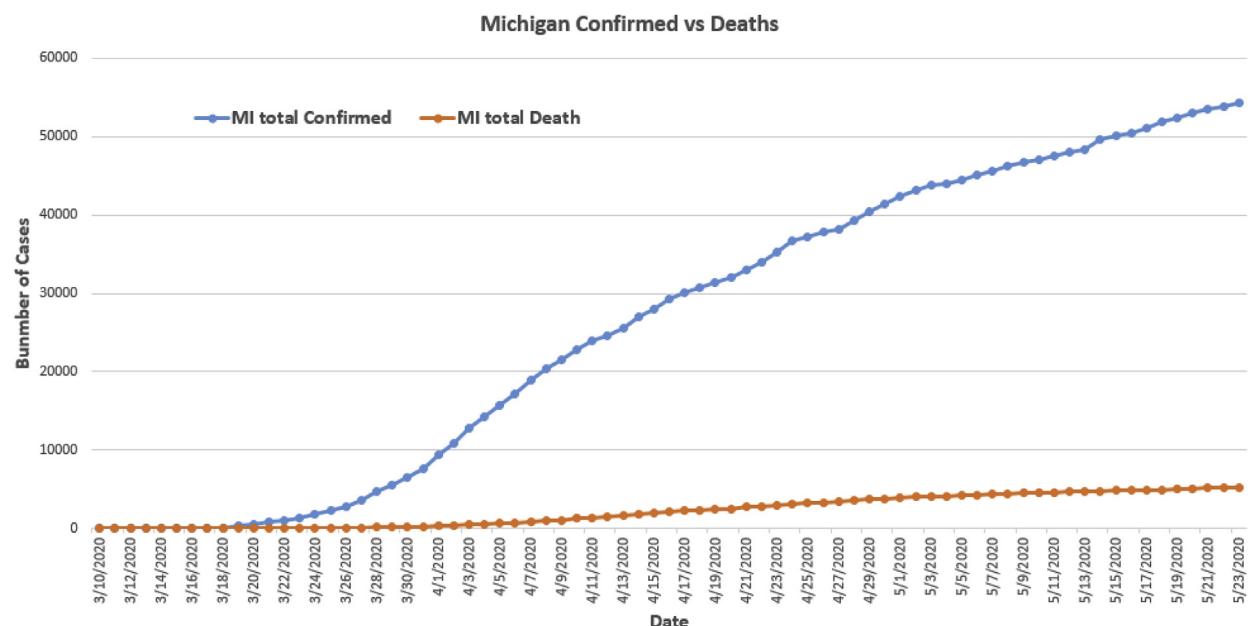


Fig. 1. Michigan daily confirmed cases and deaths.

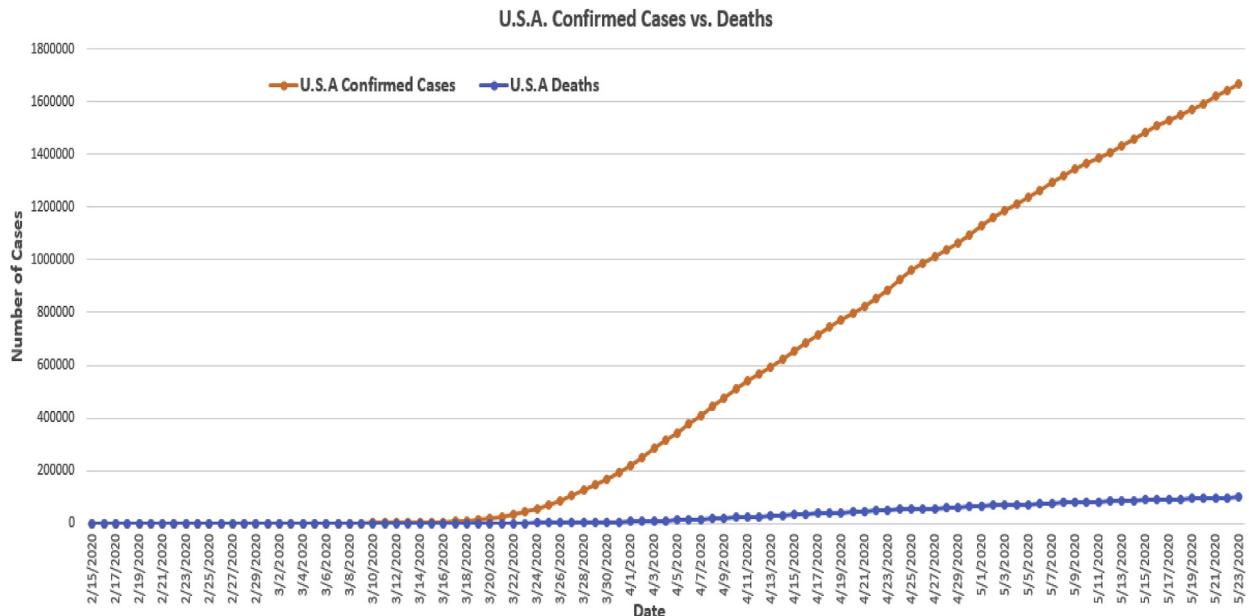


Fig. 2. The U.S.A. daily confirmed cases and deaths.

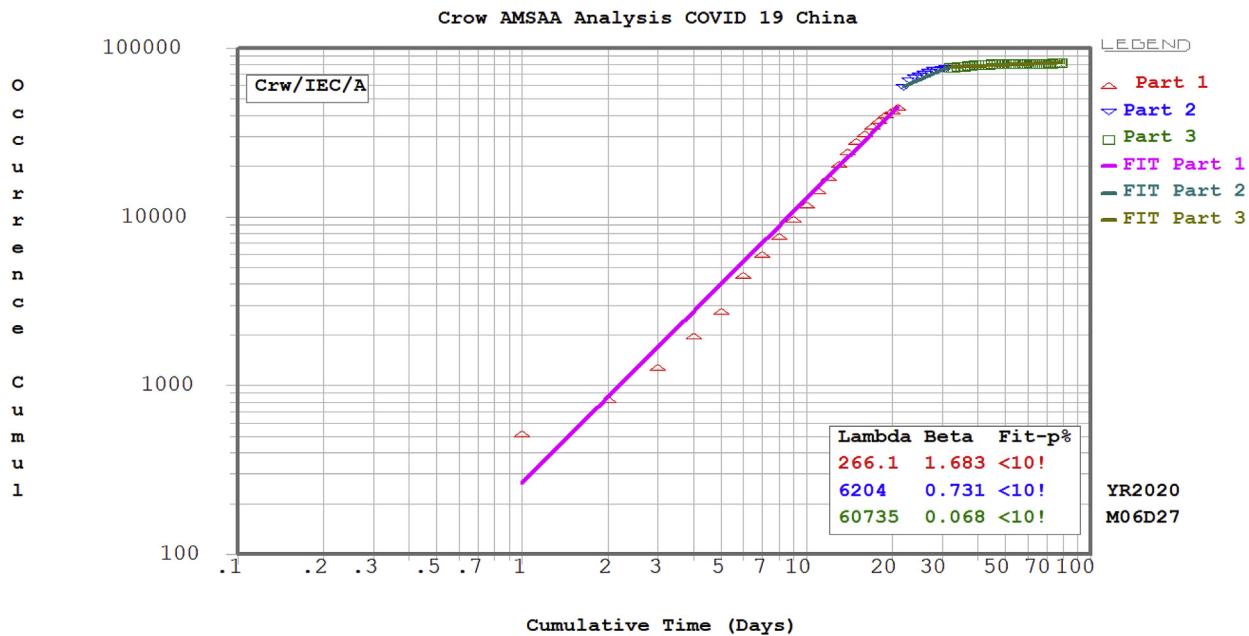


Fig. 3. The piece wise Crow-AMSAA analysis for COVID 19 – China.

at home and social distance/wearing mask policy were implemented all over the country. From the CA slope β values (phase (1) 1.683—phase (2) 0.731—phase (3) 0.068), the locking down, isolation, staying home and social distance/wearing masks played an important role to slow down the COVID19 spreading in China.

The comparison between the real infected case and the Crow-AMSAA predicted for China is shown in Fig. 4.

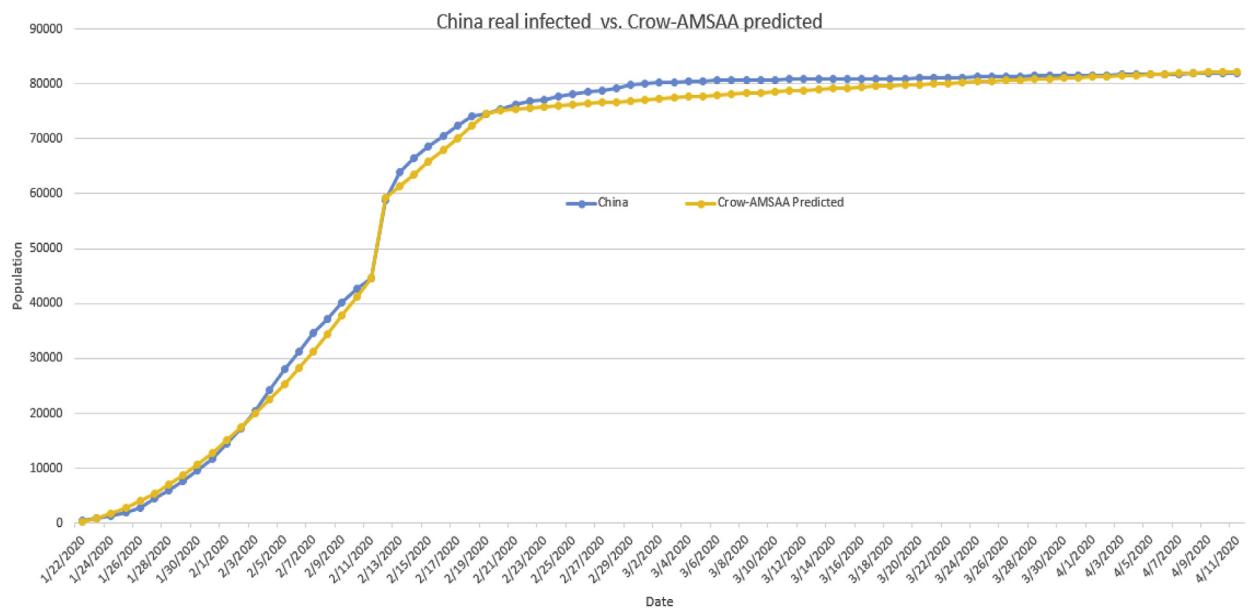


Fig. 4. The China real infected versus Crow-AMSAA predicted.



Fig. 5. The piece wise Crow-AMSAA analysis for COVID 19 Deaths – China.

The daily death rate for COVID19 in China is plotted in Fig. 5 by using CA method. The death rate also shows the three phases. The first phase (1/22/2020 to 2/23/2020) is the death rate increasing phase where CA slope β is $1.829 > 1$. The second phase (2/24/2020 to 3/3/2020) and the third phase (3/4/2020 to 4/9/2020) are the death rate decreasing phases, the CA slopes are 0.533 and 0.16 respectively.

In Michigan: The Michigan cumulative confirmed case and death are plotted in Fig. 1. The Crow-AMSAA method [equation (10) $\ln L_n$ to $\ln L_1$] also applies for Michigan cumulative total confirmed cases[Fig. 6]. The time period is from 3/10/2020 to 5/23/

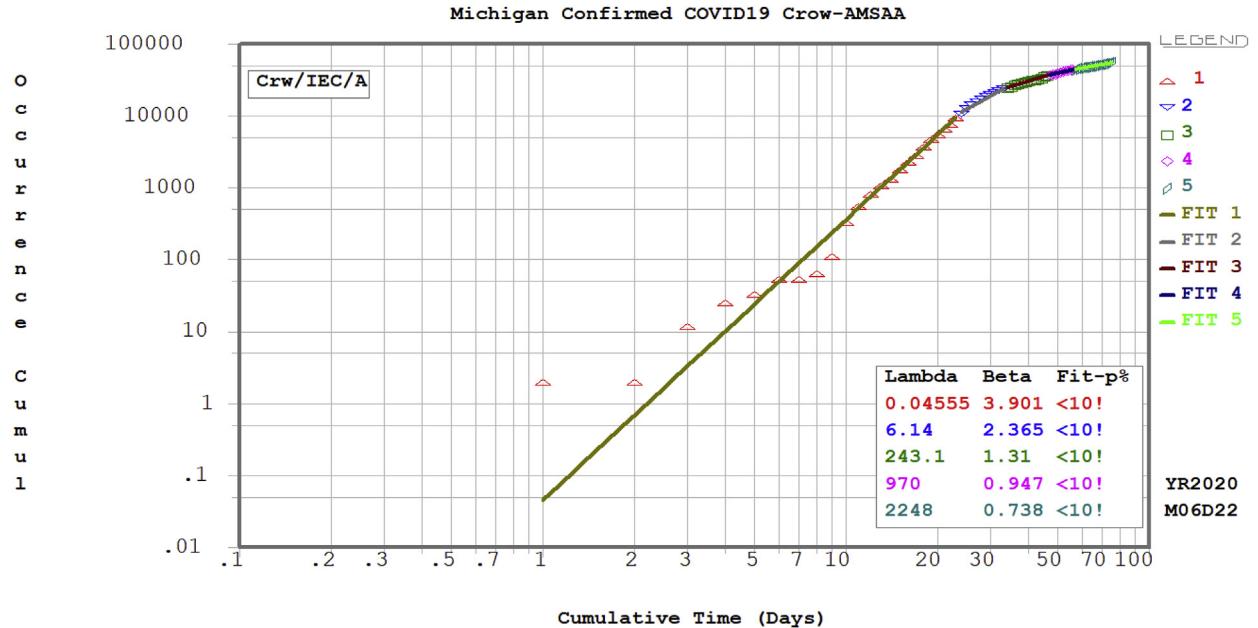


Fig. 6. The piece wise Crow-AMSAA analysis for COVID 19 —Michigan.

2020. So far, there are five pieces of the wise Crow-AMSAA lines can be applied for Michigan cases. From 3/10/2020 to 4/1/2020, the CA slope β is $3.901 > 1$, and the infectious rate is increasing dramatically. From 4/2/2020 to 4/11/2020, the CA slope β is $2.365 > 1$, and the infectious rate is still increasing, though the slope β is slight smaller than the first phase. Since 3/24/2020, Michigan Governor issued a stay home order, the order is absolutely helping the state of Michigan to slow down the spreading of the disease, because the CA slope β is still greater than 1, so the infectious rate is still increasing at a much slower rate. From 4/12/2020 to 4/24/2020, the CA slope β is $1.31 > 1$, and the infectious rate is still increasing, though the slope β is slightly smaller than the second phase. From 4/25/2020 to 5/4/2020, the CA slope β is $0.947 < 1$, and the infectious rate is decreasing. From 5/5/2020 to 5/23/2020, the CA slope β is $0.738 < 1$, and the infectious rate is still decreasing, the slope β is slightly smaller than the previous phase.

The comparison between the real infected case and the Crow-AMSAA predicted for Michigan is shown in Fig. 7. Here we assume the future CA slope β is changed as 1.5 decreasing in 15 days based on the previous history we have learned for

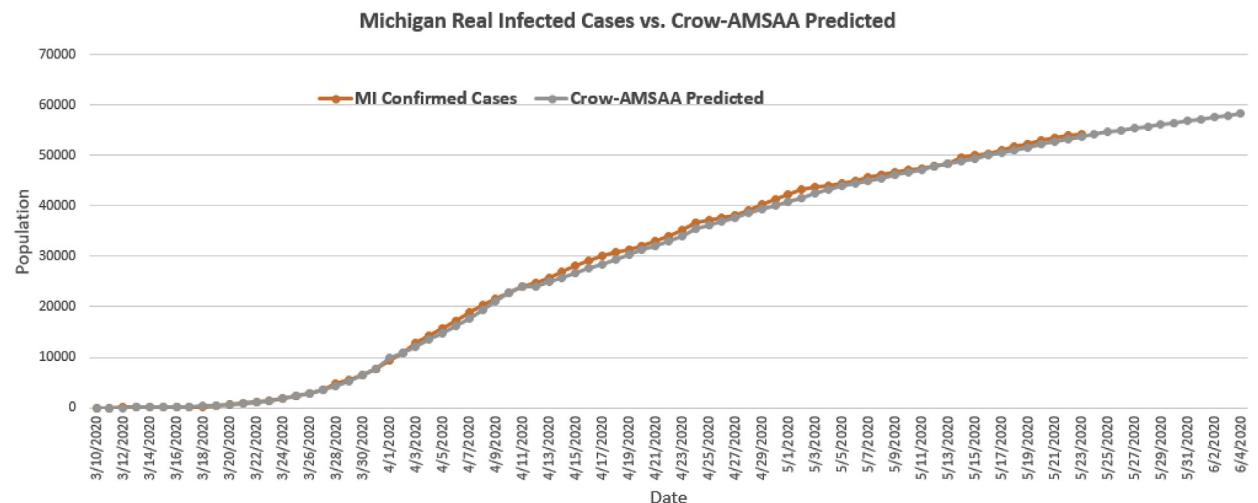


Fig. 7. The Michigan Real Infected Case versus Crow-AMSAA predicted.

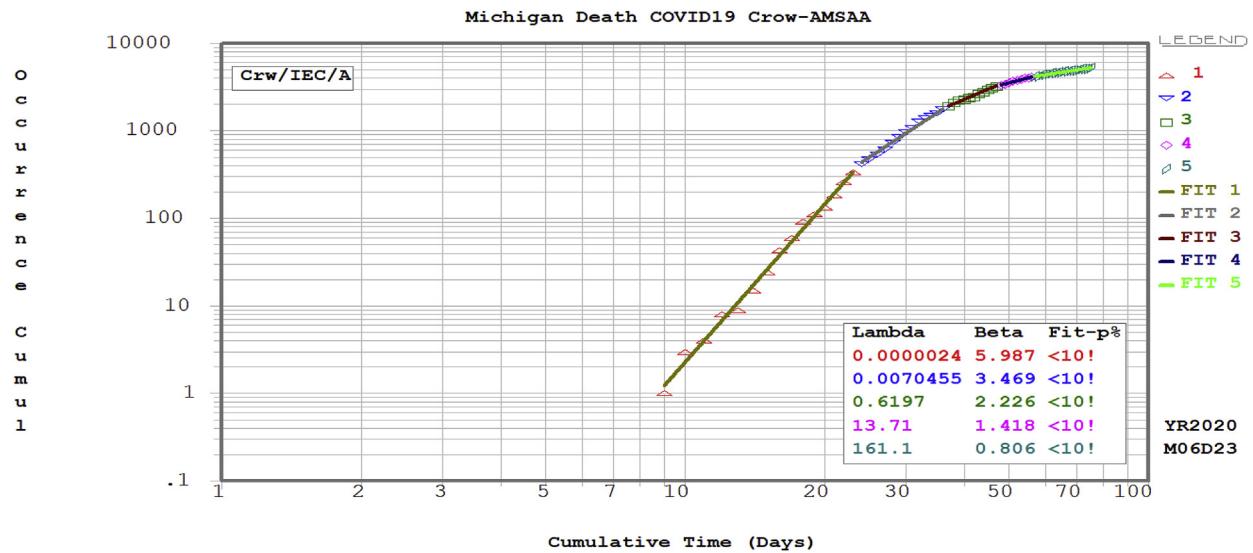


Fig. 8. The piece wise Crow-AMSAA analysis for COVID 19 Deaths –Michigan.

Michigan. But when CA slope β becomes smaller than 1, we assume the slope changing pattern like slope changing pattern in China.

The daily death rate for COVID19 in Michigan is plotted in Fig. 8 by using CA method. So far, the death rate shows the two pieces of CA plots. The first piece (3/18/2020 to 4/1/2020) is the death rate increasing phase where CA slope β is $5.987 > 1$. The death rate in the second piece (4/2/2020 to 4/14/2020) is slowing down comparing to the first phase but it remains in an increasing phase where the CA slopes β is $3.469 > 1$. The death rate in the third piece (4/15/2020 to 4/25/2020) is slowing down comparing to the second phase but it remains in an increasing phase where the CA slopes β is $2.226 > 1$. The death rate in the fourth piece (4/26/2020 to 5/4/2020) is slowing down comparing to the third phase but it remains in an increasing phase where the CA slopes β is $1.418 > 1$. The death rate in the fifth piece (5/5/2020 to 5/23/2020) is slowing down comparing to the fourth phase, and it is in a decreasing phase where the CA slopes β is $0.806 < 1$.

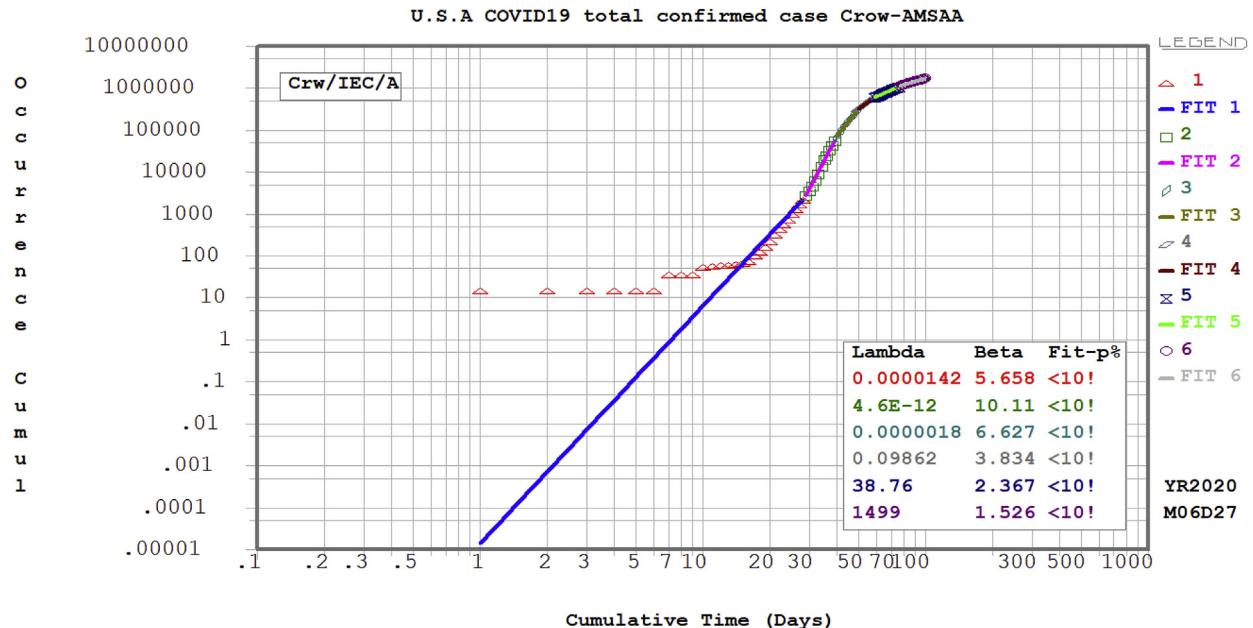


Fig. 9. The piece wise Crow-AMSAA analysis for COVID 19 –U.S.A.

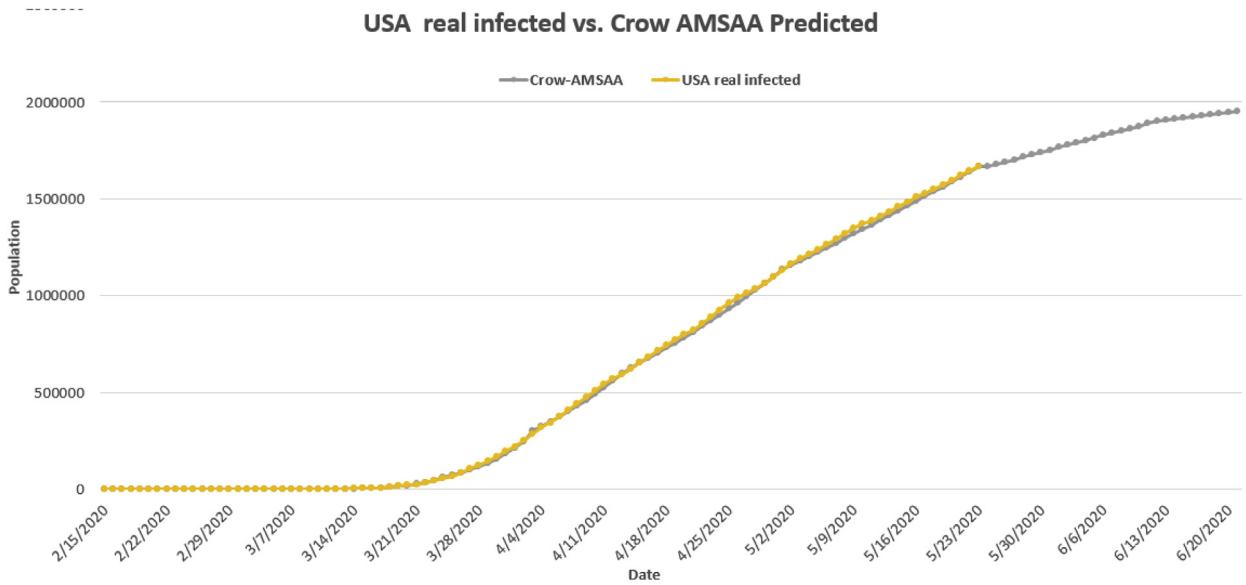


Fig. 10. USA true infected versus Crow AMSAA Predicted.

In the U.S.A.: The U.S.A. cumulative confirmed case and death are plotted in Fig. 2. The same study was conducted for U.S.A. total confirmed cases[Fig. 9]. From the piece-wise Crow-AMSAA plots, there are six phases, so far, for the U.S.A infectious cases. The first phase (2/15/2020 to 3/13/2020), the CA slope β is $5.658 > 1$, and the infectious rate is increasing. The CA slope β of the second phase (3/14/2020 to 3/24/2020) is $10.11 > 1$, the infectious rate is increasing dramatically. The CA slope β of the third phase (3/25/2020 to 4/3/2020) is $6.627 > 1$ where the infectious rate is still increasing. The CA slope β of the fourth phase (4/4/2020 to 4/12/2020) is $3.834 > 1$ where the infectious rate is still increasing, though the slope β is smaller than the third phase. The CA slope β of the fifth phase (4/13/2020 to 4/30/2020) is $2.367 > 1$ where the infectious rate is still increasing, though the slope β is smaller than the fourth phase. The CA slope β of the sixth phase (5/1/2020 to 5/23/2020) is $1.526 > 1$ where the infectious rate is still increasing, though the slope β is smaller than the fifth phase. Most of states in U.S.A have

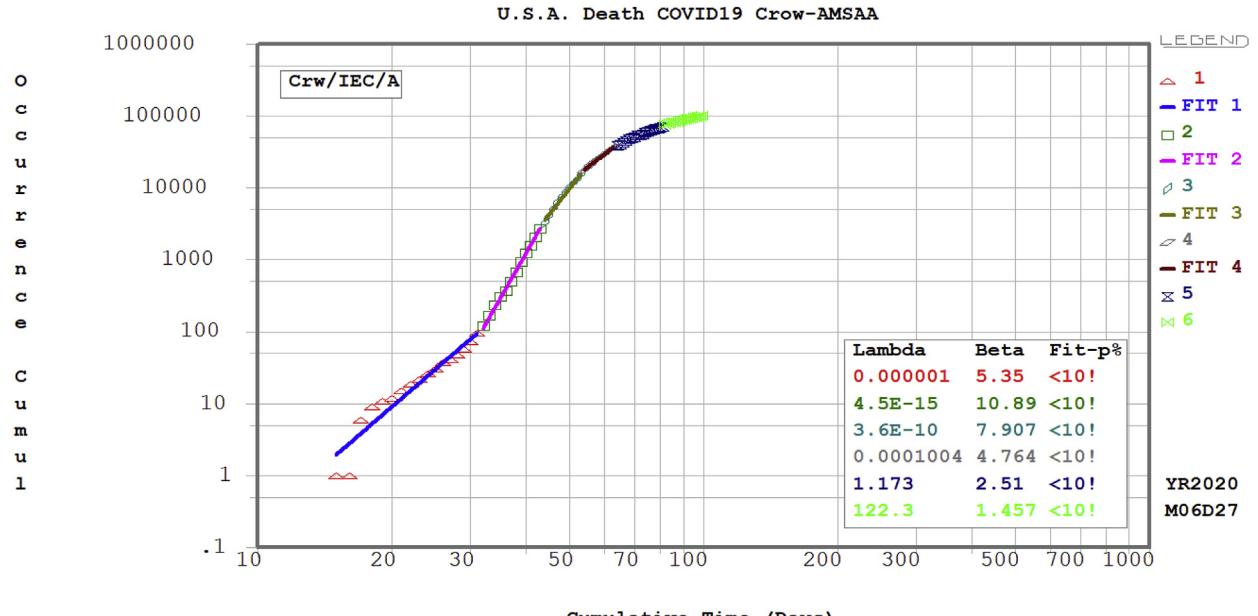


Fig. 11. The piece wise Crow-AMSAA analysis for COVID 19 Deaths –U.S.A.

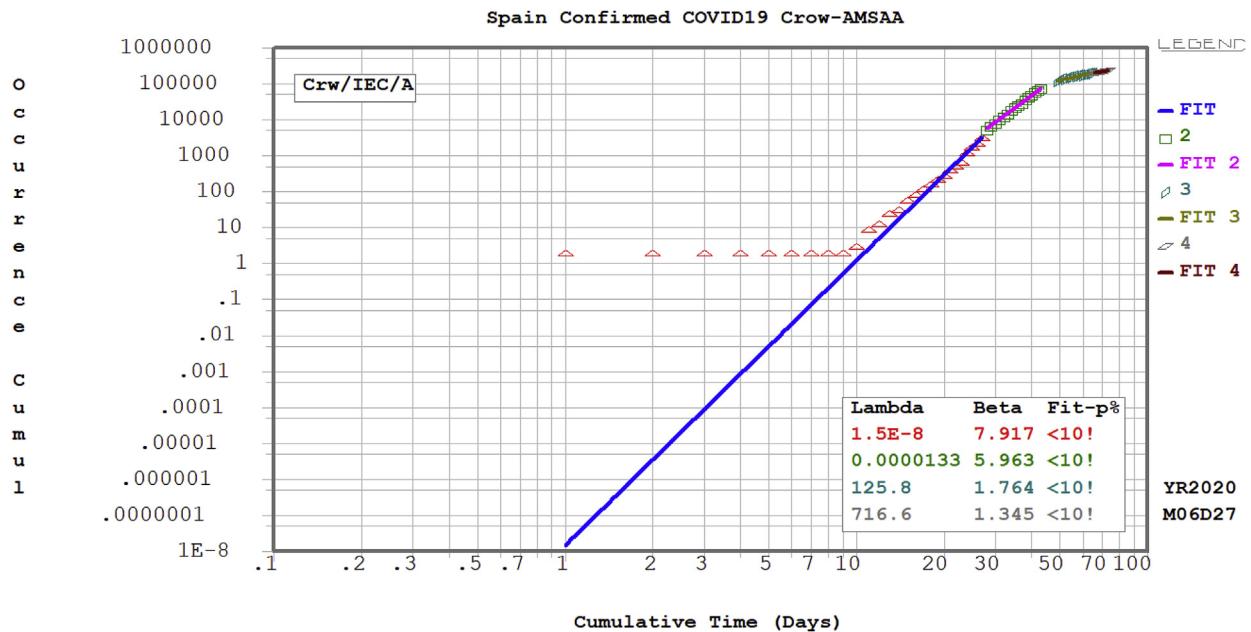


Fig. 12. The piece wise Crow-AMSAA analysis for COVID 19 –Spain.

issued the staying at home order and social distance requirement, this will help to slow down the transmission speed of the disease.

The comparison between the real infected case and the Crow-AMSAA predicted for U.S.A is shown in Fig. 10. Here we assume the future CA slope β is changed as factor 2 decreasing in 15 days based on the previous history we have learned for U.S.A. But when CA slope β becomes smaller than 1, we assume the slope changing pattern like slope changing pattern in China.

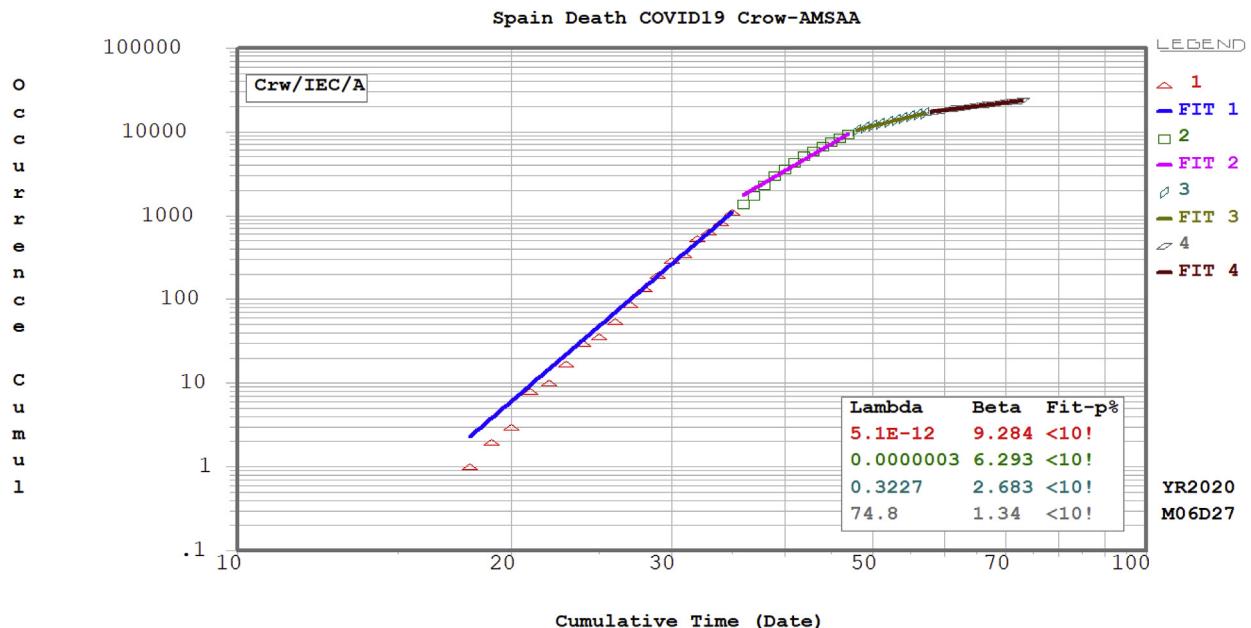


Fig. 13. The piece wise Crow-AMSAA analysis for COVID 19 Deaths –Spain.

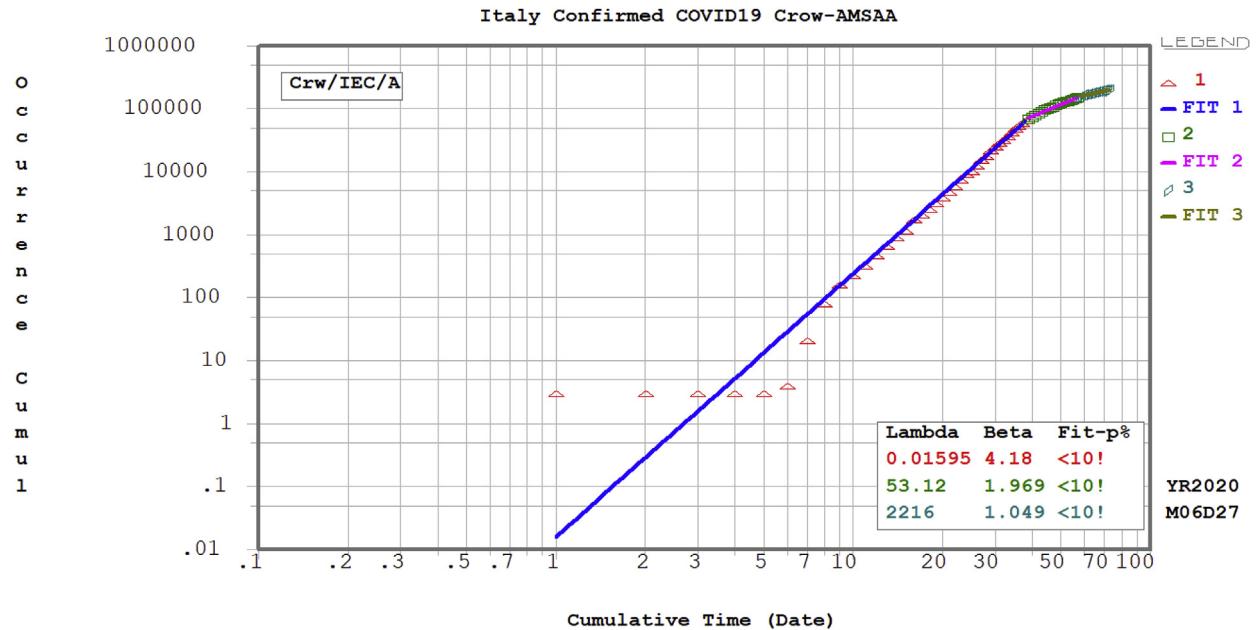


Fig. 14. The piece wise Crow-AMSAA analysis for COVID 19 –Italy.

The daily death rate for COVID 19 for U.S.A is also plotted in Fig. 11. So far there are six phases identified in the plot. The CA slope β is 5.35 for phase I (2/19/2020 to 3/16/2020). The CA slope β is 10.89 for phase II (3/17/2020 to 3/28/2020) where the death rate increasing dramatically. The CA slope β is 7.907 for phase III (3/29/2020 to 4/7/2020) where the death rate is slowing down but it is still increasing. The CA slope β is 4.764 for phase IV (4/8/2020 to 4/17/2020) where the death rate is slowing down but it is still increasing. The CA slope β is 2.51 for phase V (4/18/2020 to 5/6/2020) where the death rate is slowing down but it is still increasing. The CA slope β is 1.457 for phase V (5/7/2020 to 5/23/2020) where the death rate is slowing down but it is still increasing.

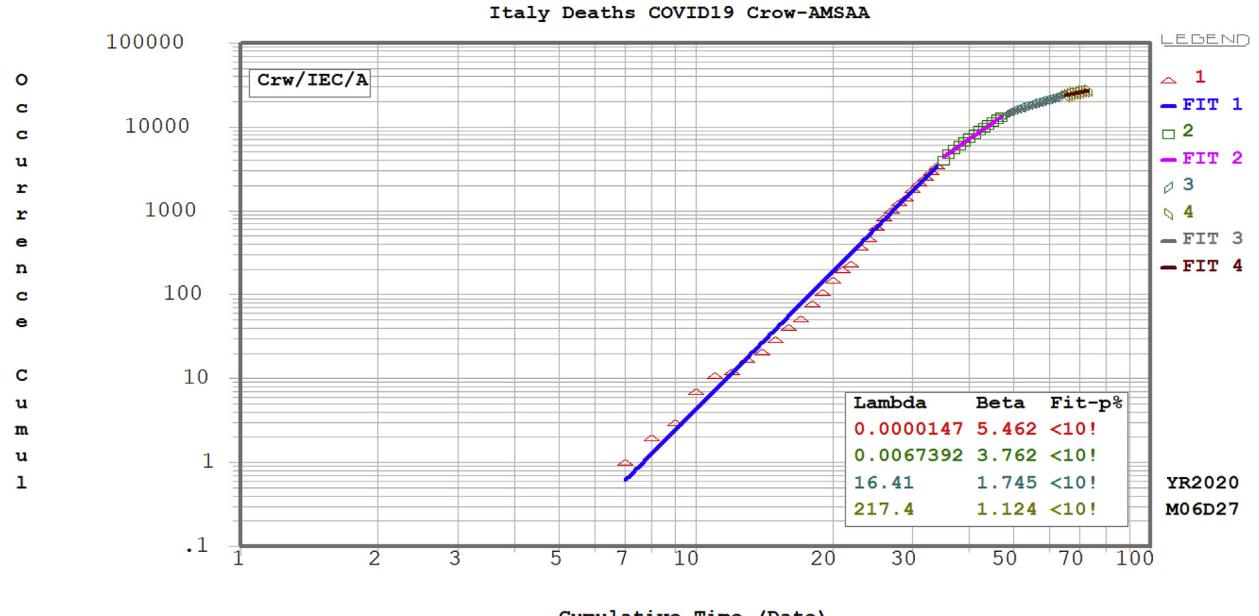


Fig. 15. The piece wise Crow-AMSAA analysis for COVID 19 Deaths –Italy.

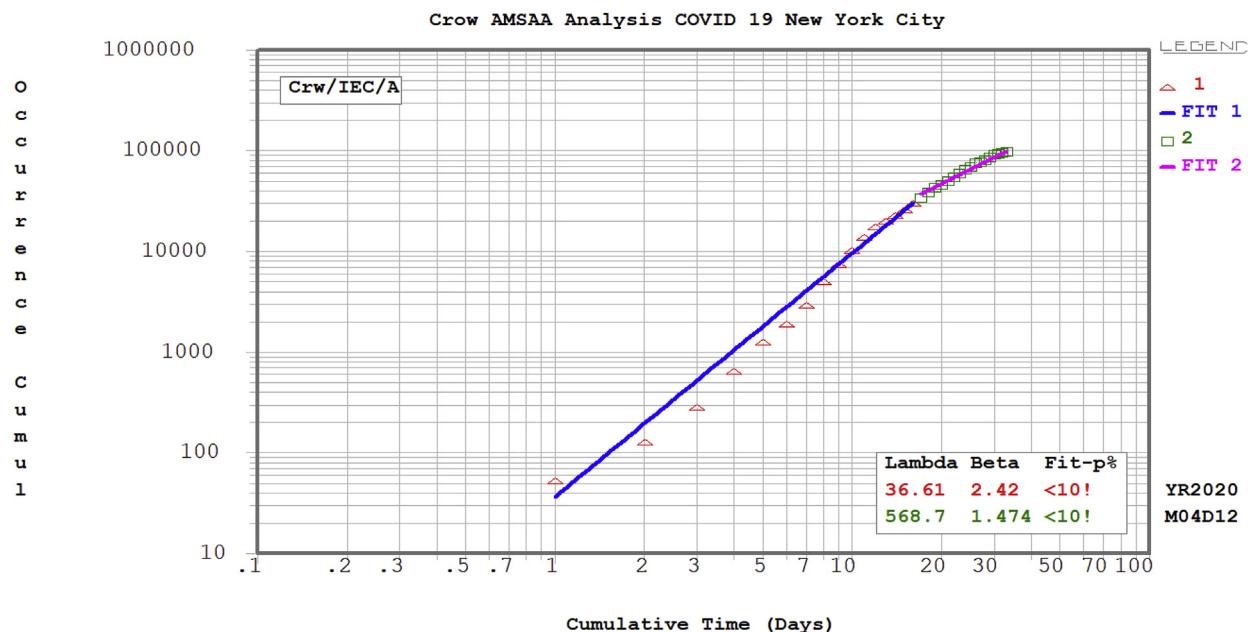


Fig. 16. The piece wise Crow-AMSAA analysis for COVID 19 –New York City.

New York City and other countries: The piece wise Crow-AMSAA analysis has been conducted for the daily confirmed cases and deaths for New York City, Spain, Italy, France, Germany, UK and South Korea [Figs. 12–25]. The slope β are summarized in Table 1. The decreasing/increasing of the infectious rate and death rate can be figured out per CA slope β values.

5. Discussion

From the Crow-AMSAA analysis above, at the beginning of the COVID 19, the infectious cases did not follow the Crow-AMSAA prediction line, but during the outbreak start, the confirmed cases does follow the CA line, the slope β value

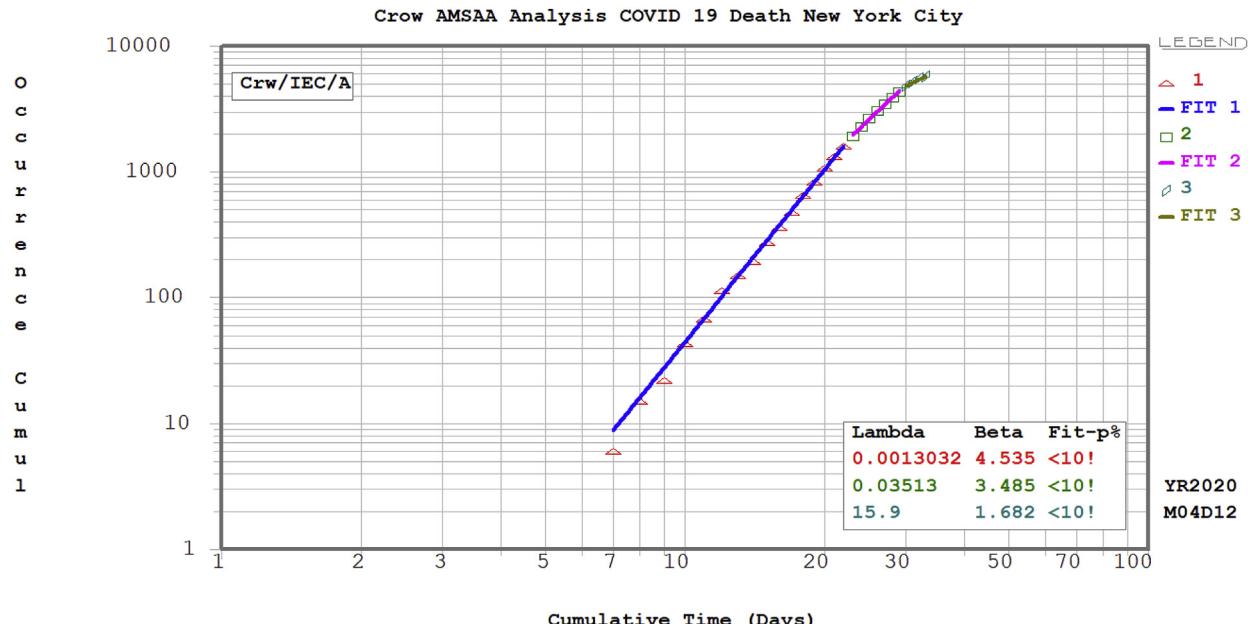


Fig. 17. The piece wise Crow-AMSAA analysis for COVID 19 Deaths –New York City.

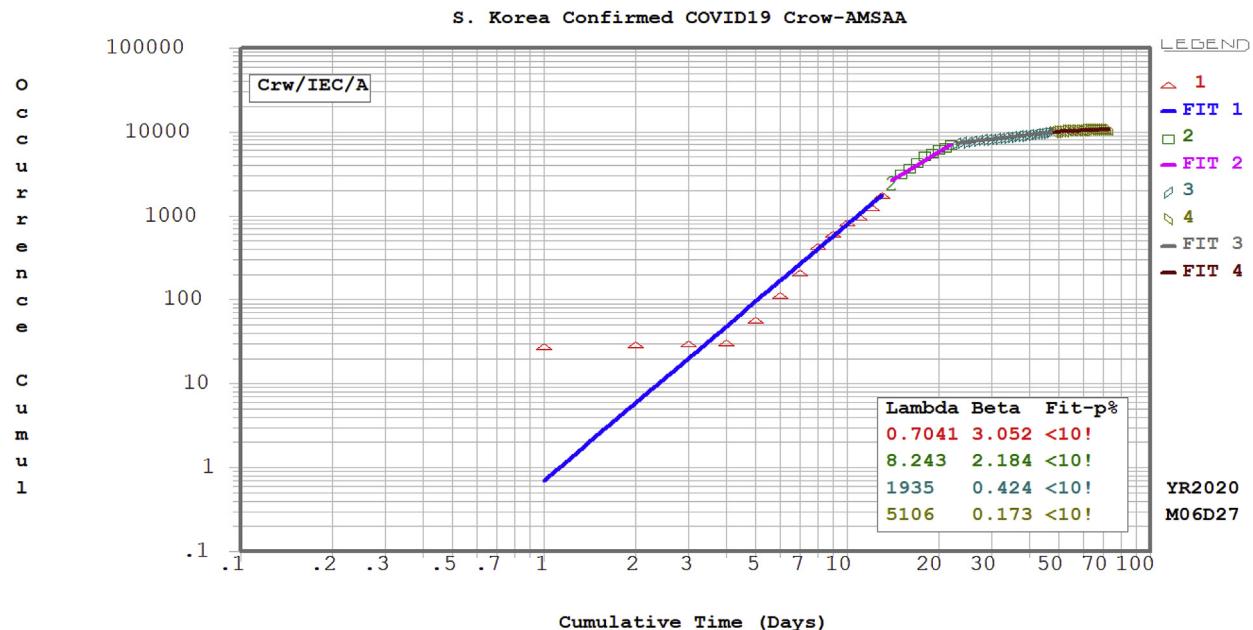


Fig. 18. The piece wise Crow-AMSAA analysis for COVID 19 –S. Korea.

indicates the pace of the transmission rate or death rate in each case. The piece wise Crow-AMSAA describes the different phases of spreading. This indicates the speed of the transmission rate could change according to the government interference, social distance order or other factors. Comparing the piece wise CA β slopes (β : 1.683–0.834–0.092) in China and in U.S.A (β : 5.658–10.11–6.627–3.834–2.367–1.526), the speed of infectious rate in U.S.A is much higher than the infectious rate in China. From the piece wise CA plots and summary Table 1 of the CA slope β , the COVID19 spreading has the different behavior at different places and countries where the government implemented the different policy to slow down the spreading.

Ranjan (Ranjan, 2020), Canabarro, etc. (Canabarro et al., 2020) and Liu, etc (Liu et al., 2020) are all using the traditional epidemiological model to predict the spreading the COVID19. This paper explores the spreading of COVID19 using a novel method – Crow-AMSAA which is borrowed from engineering reliability design. The Crow-AMSAA model is different from the

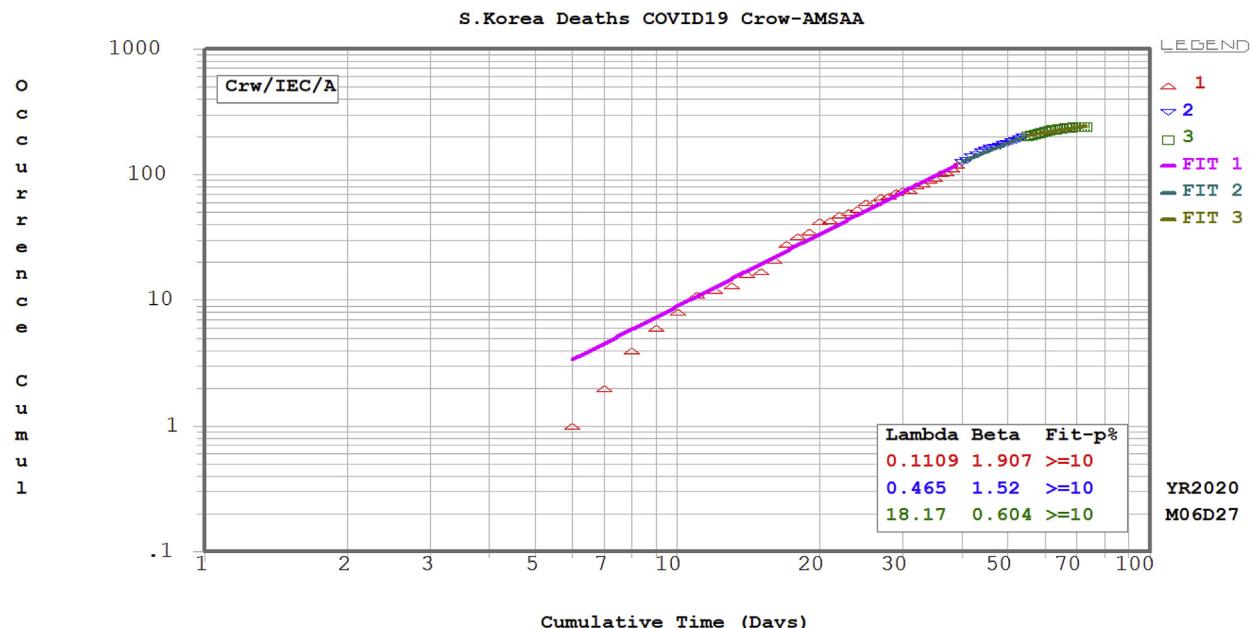


Fig. 19. The piece wise Crow-AMSAA analysis for COVID 19 Deaths –S. Korea.

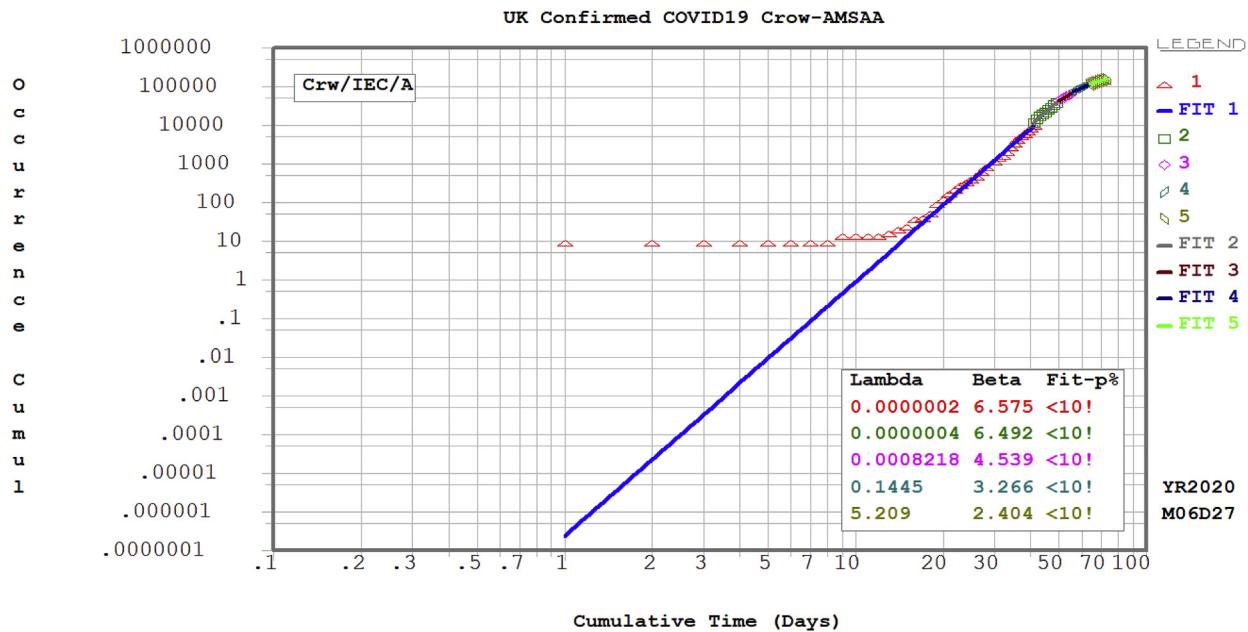


Fig. 20. The piece wise Crow-AMSAA analysis for COVID 19 –UK.

traditional epidemiological model. The Crow-AMSAA model is the Non-Homogeneous Poisson Process (NHPP), which is for a more complex problem, and NHPP models such as those for outbreaks in social networks are often believed to provide better predictions of the benefits of various mitigation strategies such as isolation, locking down and social distance (Burra & Chowellb, 2008; Cifuentes-Amado & Cepeda-Cuervo, 2015). The piece wise Crow-AMSAA plots are used to model the expected cumulative number of infected numbers over time, and the Ln-Ln plot is to simplify the curve, and slope β is calculated to indicate that the infectious rate is increasing or decreasing. The traditional epidemiological models is very difficult to

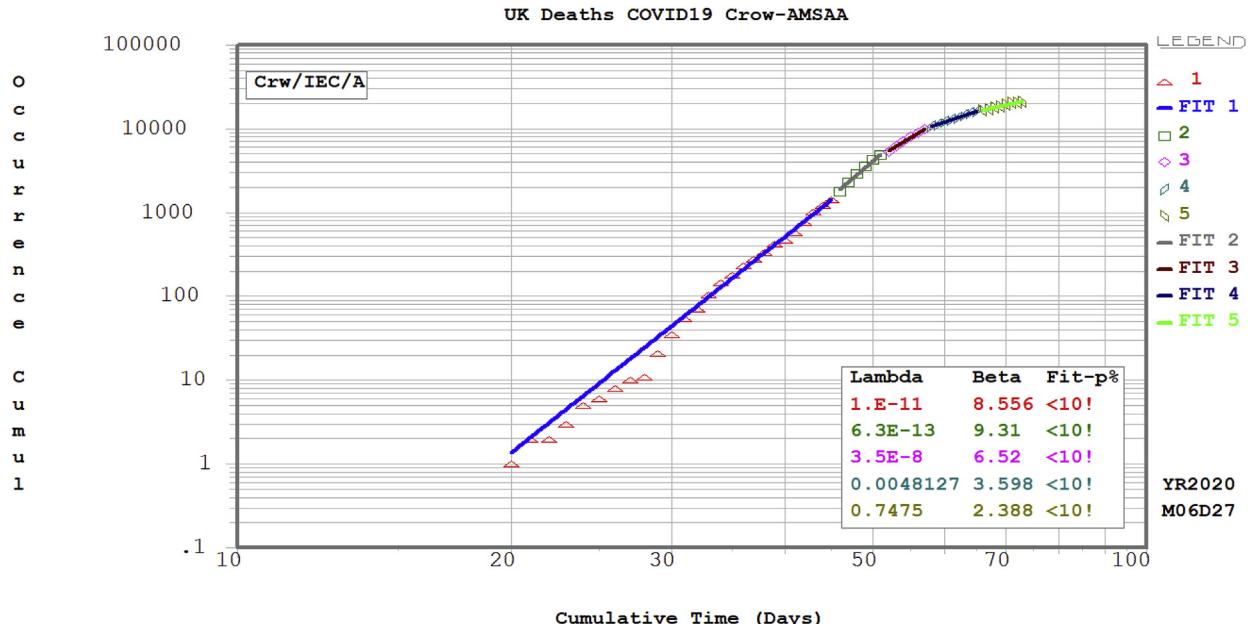


Fig. 21. The piece wise Crow-AMSAA analysis for COVID 19 Deaths–UK.

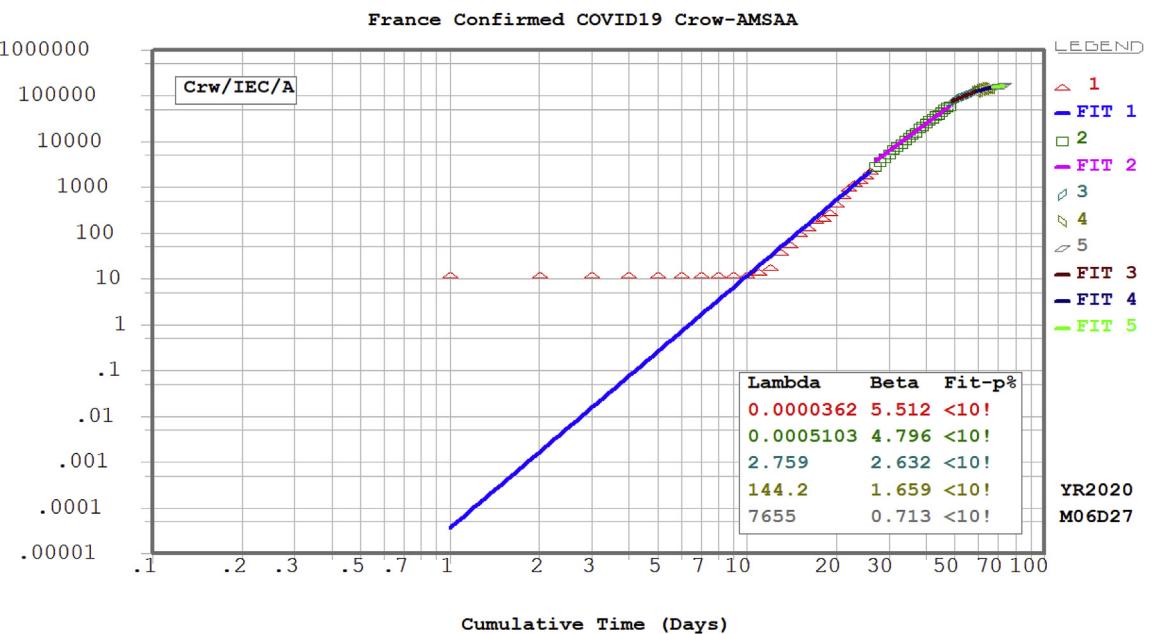


Fig. 22. The piece wise Crow-AMSAA analysis for COVID 19 –France.

predict the numbers of infections when the disease spreading enters to a new different phase, and SIR method has too many parameters and assumptions, and it is susceptible to the parameters and assumptions.

The limitation of this piece wise Crow-AMSAA method is that there is a need for a manual separation of the data to be applied to find out each different infection phase at each different time period. The good fit of the data is depending on good data separation.

Future work: More studies should be done in the future for COVID19 that include data for the distribution of demographical, zone, age, race and climate conditions by using the piece wise CA models. Also there should be studies that focus on

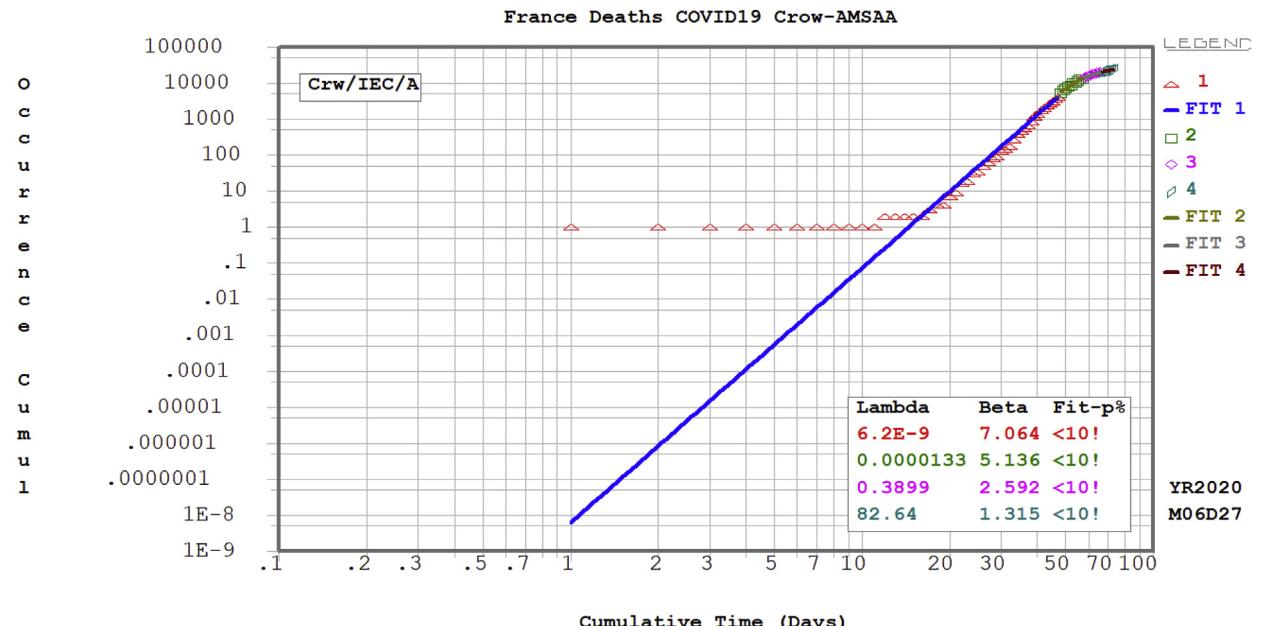


Fig. 23. The piece wise Crow-AMSAA analysis for COVID 19 Deaths –France.

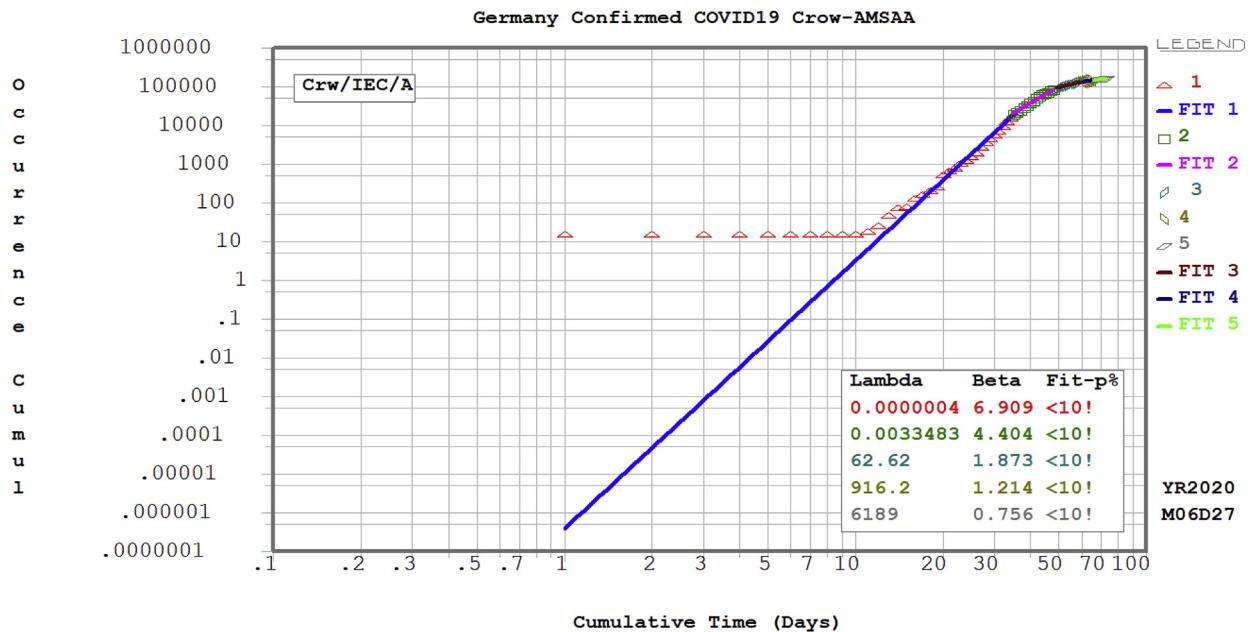


Fig. 24. The piece wise Crow-AMSAA analysis for COVID 19 –Germany.

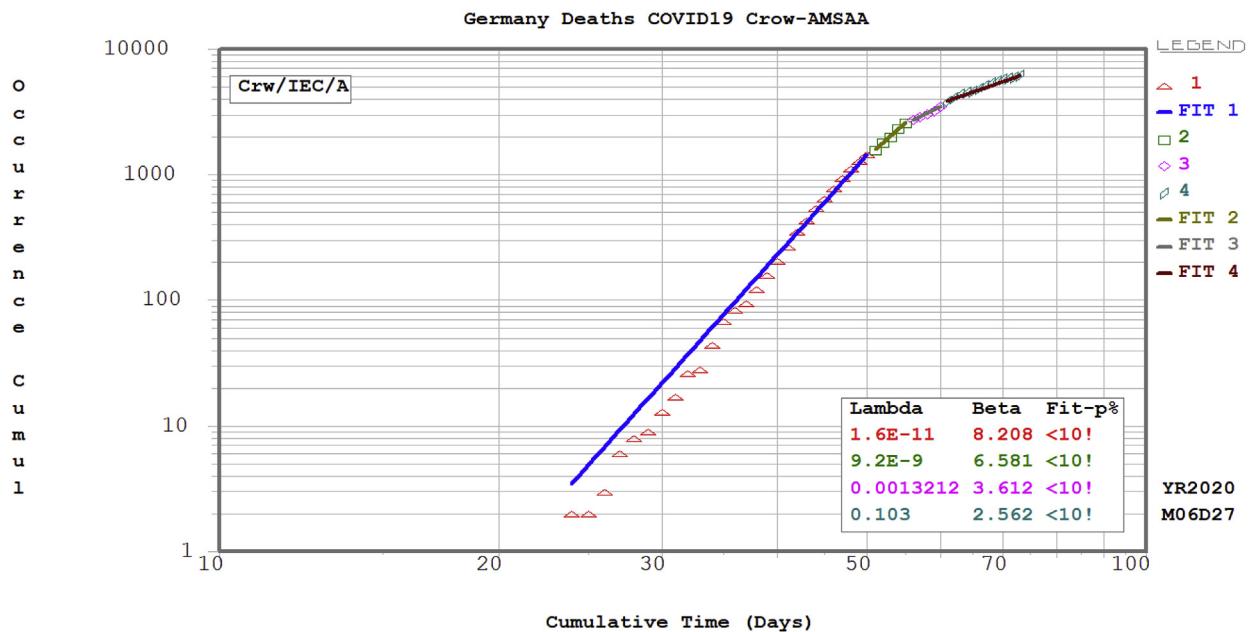


Fig. 25. The piece wise Crow-AMSAA analysis for COVID 19 Deaths –Germany.

the effectiveness of policy (government, industrial, social) which prevent the spreading of this disease, and the data studied to of how the CA slope β is affected understand effects.

6. Conclusion

From the analysis of data and conclusions from confirmed cases and deaths of COVID19 in Michigan, New York city, U.S.A, China and other countries, the piece wise Crow-AMSAA method can be used to modeling the spreading of COVID19.

Declaration of competing interest

Table 1Summary of Crow-AMSAA slope β for different places at different phases.

$\beta > 1$ rate increasing, $\beta < 1$ rate decreasing, current $\beta <$ previous β , the rate slow down, current $\beta >$ previous β , the rate speed up			
	Infectious slope β	Death Slope β	Comment
U.S.A	Phase 1 5.658	5.35	Infectious rate slow down. Death rate slow down (data is from 2/15/2020 to 5/23/2020)
	Phase 2 10.11	10.89	
	Phase 3 6.627	7.907	
	Phase 4 3.834	4.764	
	Phase 5 2.367	2.51	
	Phase 6 1.526	1.457	
Spain	Phase 1 7.917	9.284	Infectious rate slow down. Death rate slow down (data is from 2/15/2020 to 4/27/2020)
	Phase 2 5.963	6.293	
	Phase 3 1.764	2.683	
	Phase 4 1.345	1.34	
Italy	Phase 1 4.18	5.462	Infectious rate slow down. Death rate slow down (data is from 2/15/2020 to 4/27/2020)
	Phase 2 1.969	3.762	
	Phase 3 1.049	1.745	
	Phase 4 N/A	1.124	
France	Phase 1 5.512	7.064	Infectious rate decreasing. Death rate slow down (data is from 2/15/2020 to 4/27/2020)
	Phase 2 4.796	5.136	
	Phase 3 2.632	2.592	
	Phase 4 1.659	1.315	
	Phase 5 0.713	N/A	
Germany	Phase 1 6.909	8.208	Infectious rate decreasing. Death rate slow down (data is from 2/15/2020 to 4/27/2020)
	Phase 2 4.404	6.581	
	Phase 3 1.873	3.612	
	Phase 4 1.214	2.562	
	Phase 5 0.756	N/A	
UK	Phase 1 6.575	8.556	Infectious rate slow down. Death rate slow down (data is from 2/15/2020 to 4/27/2020)
	Phase 2 6.492	9.31	
	Phase 3 4.539	6.52	
	Phase 4 3.266	3.598	
	Phase 5 2.404	2.388	
China	Phase 1 1.683	1.829	Infectious rate decreasing. Death rate decreasing (data is from 1/22/2020 to 4/11/2020)
	Phase 2 0.731	0.533	
	Phase 3 0.068	0.16	
S. Korea	Phase 1 3.052	1.907	Infectious rate decreasing, Death rate decreasing(data is from 2/15/2020 to 4/27/2020)
	Phase 2 2.184	1.52	
	Phase 3 0.424	0.604	
	Phase 4 0.173	N/A	
Michigan	Phase 1 3.901	5.987	Infectious rate decreasing. Death rate decreasing (data is from 3/10/2020 to 5/23/2020)
	Phase 2 2.365	3.469	
	Phase 3 1.31	2.226	
	Phase 4 0.947	1.418	
	Phase 5 0.738	0.806	
New York City	Phase 1 2.42	4.535	Infectious rate slow down. Death rate slow down (data is from 3/9/2020 to 4/10/2020)
	Phase 2 1.474	3.485	
	Phase 3 N/A	1.682	

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.idm.2020.07.001>.

References

Abernethy, R. B. (2006). *The new Weibull handbook*. Fifth Addition.

- Burra, T. L., & Chowell, G. (July 2008). Signatures of non-homogeneous mixing in disease outbreaks. *Mathematical and Computer Modelling*, 48(1–2), 122–140.
- Canabarro, A., Ten_orio, E., Martins, R., Martins, L., Brito, S., & Chaves, R. (2020). Data-driven study of the COVID-19 pandemic via age-structured modelling and prediction of the health system failure in Brazil amid diverse intervention strategies. *medRxiv*. <https://doi.org/10.1101/2020.04.03.20052498>. preprint.
- Cifuentes-Amado, M., & Cepeda-Cuervo, E. (2015). Non-homogeneous Poisson process to model seasonal events: Application to the health diseases. *International Journal of Statistics in Medical Research*, 4, 337–346.
- Click On Detroit News. <https://www.clickondetroit.com/news/local/2020/03/20/michigan-covid-19-data-tracking-case-count-cases-by-county-deaths-cases-by-age-tests/>.
- Guo, H., Mettas, A., Sarakakis, G., & Niu, P. (2010). Piecewise NHPP models with maximum likelihood estimation for repairable systems. In *2010 reliability and maintainability symposium, san Jose, CA, USA, January 25- 28*.
- IEC 61164 Ed 2.0 en. (2004). *Reliability growth - statistical test and estimation methods*.
- Liu, Z., Magal, P., & Webb, G. (2020). Predicting the number of reported and unreported cases for the COVID-19 epidemics in China, South Korea, Italy, France, Germany and United Kingdom. *medRxiv*. <https://doi.org/10.1101/2020.04.09.20058974>. preprint.
- Ma, J. (2020). Estimating epidemic exponential growth rate and basic reproduction number. *Infectious Disease Modelling*, 5, 129–141.
- New York City Gov. <https://www1.nyc.gov/site/doh/covid/covid-19-data.page>.
- Ranjan, R. (2020). Predictions for COVID-19 outbreak in India using epidemiological models. *medRxiv*. <https://doi.org/10.1101/2020.04.02.20051466>. preprint.
- Tananko, D. E. (2020). Practical guide to reliability growth analysis. In *Annual RELIABILITY and MAINTAINABILITY symposium*.
- Wang, Q., Xie, S., Wang, Y., & Zeng, D. (2020). Survival-convolution models for predicting COVID-19 cases and assessing effects of mitigation strategies. <https://doi.org/10.1101/2020.04.16.20067306> medRxiv preprint.
- WorldOMeters. <https://www.worldometers.info/coronavirus/country/us/>.