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Covid-19 Statistics, Strange trend and Forecasting of Total Cases in the most Infected African Countries: An ARIMA and Fuzzy Time Series Approaches

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Abstract. The current event in the world is corona-virus; the spread of this virus can put all countries in situation of incapacity of how manage and face. This article focused on the class of ARIMA models and Fuzzy Time Series. The techniques are applied to trajectory Corona virus on three African countries: Algeria, Egypt and South Africa over the period (2020-02-15 /2020-03-19). Although the hyper stochastic of this pandemic, it is seen that ARIMA models fits well the trajectory of Covid-19. We predict a continuous trend of virus spreading in next days, a fact that alert the governments of theses countries and the whole African countries for further strengthen prevention and intervention policies to combat this epidemic.

Key words: Time Series; Fuzzy Time Series ; Corona virus.
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Résumé (French Abstract) L'événement de jour dans le monde est le virus corona; la propagation de ce virus peut mettre tous les pays en situation d'incapacité à gérer et à faire face. Cet article portait sur la classe des modèles ARIMA et les séries temporelles à logique floues. Ces deux techniques sont appliquées à la trajectoire du virus Corona dans trois pays africains: l'Algérie, l'Égypte et l'Afrique du Sud sur la période (2020-02-15 / 2020-03-19). Bien que l'hyper stochastique de cette pandémie, on voit que les modèles ARIMA correspondent bien à la trajectoire de Covid-19. Nous prévoyons une tendance continue à la propagation du virus dans les prochains jours, un fait qui alertera les gouvernements de ces pays et l'ensemble des pays africains pour renforcer encore les politiques de prévention et d'intervention pour lutter contre cette épidémie.

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1. Introduction

The World Health Organization (WHO) has declared the epidemic of the new coronavirus to be a pandemic as health authorities around the world continue to struggle to contain the disease, which was first detected in the central city of Wuhan. The virus, which causes a respiratory disease called COVID-19, has spread to at least 146 countries and territories on six continents, infecting more than 164,000 people and killing more than 6,400. The vast majority of infections and deaths are occurred in mainland China, where authorities have detained an area of 60 million people to contain the pathogen.

Africa is not spared the spread of this virus, recent studies put it in first rank of high risk region for contamination, see mainly Gilbert *et al* (2020). And although Africa's handling of the pandemic has received scant global attention so far, experts worry the virus may ravage countries with weak health systems and a population disproportionately affected by HIV, tuberculosis (TB), and other infectious diseases. *social distancing* will be hard to do in the continent's overcrowded cities and slums. Science (2020). The same situation have been highlighted with Pandemic influenza in this continent as Sambala et *al* (2018) asked in their study: Are we ready yet ?.

The most dangerous effects of this virus are: *First*, public health problems, and we see clearly how the virus of Ebola how can damaged these countries, Marston et *al* (2017). The same case with HIV/AIDS and the well estabished nexus with poverty and economics vulnerability, see Masanjala (2007), *Second*, Economics vulnerability in a continent where their countries almost live under the threshold of poverty, see for instance, Andrimihaja et *al* (2011) and Cilliers Sisk (2013).

For Gilbert *et al* (2020), when they ranked African countries according to risk of spread virus, the first three ranked were : Egypt, Algeria and South Africa. Unfortunately, the updating statistics of incidence confirm such result. In this context we are really worry of the coming days, and months, every body now over world, and especially in these three African countries, ask the question: **what's the trend of this virus ?** under this serious question ,we will trying to give a response by using the statistical methods such Box-Jenkins,and Fuzzy Time series (FTS) on three countries: Algeria, Egypt and South Africa.

For the box-jenkins methods, a variety of application have been done in epidemiology and public health, Promprou et *al* (2006), applied this method for forecasting Dengue Haemorrhagic fever cases in Southern Thailand. In epedimic situation, Earnest et *al* (2005) using ARIMA models in a tertiary hospital in Singapore to predict and monitor the number of beds occupied during a SARS outbreak. For modelling the time series of malaria in Afghanistan, Anwar et *al* (2016) have been based on ARIMA models to predict the future trends and incidence . For the fuzzy time series approach, we found a little studies used it in health and epidemiology fields, we note the study of **?**, they analysed the infectious disease surveillance data using this method, in a recent study, Tricahya and Rustam (2019), tried to forecast the amount of Pneumonia Patients in Jakarta.

We deal with these methods for modelling and forecasting the trend of number of contamination, by using the R, precisely, we used *forecast* package for ARIMA models and *AnalyzeTS* for FTS method, the end of using both together is to select the best approach in term of forecasting accuracy. The rest of this paper is organized as : the section (2) is for presented a brief introduction of statical methods (ARIMA and FTS), section(3) showed the results and discussion of modelling and forecasting process on data and the section(4) summarize this study.

2. Methods

2.1. Traditional ARIMA models

ARMA models (Autoregressive – moving-average), are the main time series models representing random stationary processes. Hyndman and Athanasopoulos (2018), this method have been developed by Box and Jenkins (1970), for modelling univariate series tha; it is based on the notion of the $ARIMA$ process, in practice, this technique has three stages: identification, estimation and validation steps.

2.1.1. Auto-Regressive Model, $AR(p)$

The conditional approach in eq(1)the provides a decomposition prediction error, according to which:

$$y_t = E(y_t \diagdown y_{(t-p)}) + \epsilon_t \Leftrightarrow y_t = \sum_{i=1}^{p} \beta_i y_{t-i} + \epsilon_t \tag{1}$$

Where : $E(y_t \diagdown y_{(t-p)}$, is the component of y_t, that can give rise to a forecast, when the history of the process, $y_{t-1}, y_{t-2}, ..., y_0$ are known. And ϵ_t, represents unpredictable information. We suppose, $\epsilon_t \rightsquigarrow WN(0, \sigma^2)$, is white noise process. The equation above represents an autoregressive model (AR) of order$p$.The value y_t depends only on its p predecessors. Its properties are functions of β_i which are factors of inertia. Autoregressive processes $AR(p)$ assume that each observation y_t can be predicted by the weighted sum of a set of previous observations $y_{t-1}, y_{t-2}, ..., y_{t-p}$, plus a random error term.

Note that an auto-regressive process will only be stable if the parameters are within a certain range; for example, if there is only one autoregressive parameter, it must be in the range $-1 < \beta_1 < +1$.

2.1.2. Moving-Average process $MA(q)$

The other type of process of the box-jenkins approach is the Moving Average noted $MA(q)$.The moving average processes assume that each observation y_t is a function of the errors in the preceding observations, $\epsilon_{t-1}, \epsilon_{t-2}, ..., \epsilon_{t-q}$, plus its own error. A moving average process is given as:

$$y_t = \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \tag{2}$$

2.1.3. Auto-Regressive Moving-Average process, $ARMA(p, q)$

The combination of the two models, in equations (1) and (2) give us an $ARMA(p, q)$ process; which is the most popular models of the Box Jenkins for its flexibility and suitability for various data types. The model is designed as follow:

$$ARMA(p, q) : (1 - \sum_{i=1}^{p} \beta_i L^i) y_t = (1 + \sum_{i=1}^{q} \theta_i L^i) \epsilon_t \tag{3}$$

With: $\beta_i, i : 1, .., p$. and $\theta_i, i : 1, ..., q$ all $\in \; R$. and L: is the lag operator. The time series y_t must be stationary to be fitted by an ARMA models. We take the case of weak stationary. When one or more stationary conditions are not met, the series is said to be non-stationary. This term, however, covers many types of non-stationary, (no-stationary in trend, stochastically non-stationary,. . .), we focused on the later. Thus, if y_t is a stochastically non-stationary, a difference stationary technique should be applied; so, we have now that the polynomial $\left(1-\sum_{i=1}^{p}\beta_i L^i\right)$ has a unit root (a factor $(1-L)$) of multiplicity d, we found an $ARIMA(p,d,q)$Then it can be rewritten as:

$$\left(1-\sum_{i=1}^{p}\alpha_i L^i\right)=\left(1-\sum_{i=1}^{p-d}\phi_i L^i\right)(1-L)^d. \tag{4}$$

Consequently, a series is stationary in difference if the series obtained by differentiating the values of the original series is stationary. Generally, we used the KPSS test, Kwiatkowski et *al* (1992), ADF test, Fuller (1976).

2.1.4. Brief overview of Box-jenikns strategy

The first step is to identify the$ARIMA(p,d,q)$ model that could spawn the series. It consists, first of all, in transforming the series in order to make it stationary (the number of differentiations determines the order of integration:d), and then to identify the $ARMA(p,q)$ of the series transformed with the correlogram and partial correlogram. The graph of autocorrelation (correlogram) and partial autocorrelation coefficients (partial correlogram) give information on the order of the ARMA model, under this point , we focus on information criterion, a useful criterion is the *Akaike information criterion* (AIC), Akaike (1974) . It is written as:

$$\text{AIC}=-2\log(L)+2(p+q+k),$$

where $\mathcal{L}L$: is the likelihood of the data,$p$is the order of the autoregressive part and q is the order of the moving average part. The k represents the intercept of the$ARIMA$ model. We can use also, the Bayesian information criterion, Schwarz (1978) defined as:

$$BIC=AIC+(\log(T)-2)(p+q+k).$$

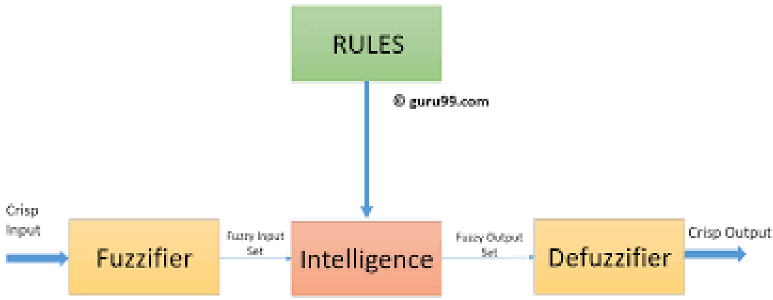
The objective is to minimize these information criterion AIC, or BIC values for a good model. To estimate the $ARIMA$ model, generally, we use a non-linear method (non-linear least squares or maximum likelihood). These methods are applied using the degrees p,d and q found in the identification step. Generally, we use the Likelihood Maximum method; by consider that the errors follow a normal distribution; $\epsilon \rightsquigarrow N(0,\sigma^2)$.

In the validation step we check whether the estimated model reproduces the model that generated the data. For this purpose, the residuals obtained from the estimated model are used to check whether they behave like white noise errors using a ”portmanteau” test (a global test that makes it possible to test the hypothesis of independence of residues). The common tests are based on residuals analysis for normality, and autocorrelation: Box and Pierce (1970), Ljung and Box (1978). We test Homoskedasticity: ARCH Test, Engle (1982). The last point under this step is the prediction of future values of y_t by the selected optimal model.

2.2. Fuzzy time series models

By its numerical aspects, fuzzy logic is opposed to modal logics. Formalized by Zadeh (1965), an artificial intelligence tool, it is used in fields as varied as Fuzzy logic (FL) is a multi-valued logic where the truth values of variables - instead of being true or false - are reels between 0 and 1. In this sense, it extends classical Boolean logic with partial truth values. The FL method imitates the way of decision making in a human which consider all the possibilities between digital values T and F. The fuzzy logic is considered as a support of decision making,

Fig. 1. The Fuzzy Logic Architecture.



This technique has been applied to different fields, from control theory to AI. The diagram of a fuzzy system is shown in Figure 1. The system has as input a precise value (x_t), the latter is fuzzified (transformed into degree of membership in the input fuzzy set, see Definition (1) below; then it is transmitted to the fuzzy inference engine. Using the fuzzy IF-THEN rules stored in the rule base, the inference engine produces a fuzzy value that will be defuzzified giving the result (Á) to be usable.

Theoretical overview on Fuzzy time series.
In this section, we briefly present some concepts of fuzzy time series. We mainly based on: Chen (1996), Huarng (2001) and Chen and Hsu (2004). The main difference between the fuzzy time series and classical time series is that the values of the former are fuzzy sets while the values of the latter are real numbers. For the FTS technique, the main advantage is that there are no assumptions considered for the data set. A good description of the main models of FTS was given by:Song and Chissom (1993).

Definition 1

We put Ω the universe of discourse;$\omega = u_1, u_2, \ldots, u_n$; we define a fuzzy set $M$of U as:

$$M = \{\frac{u_M(\mu_1)}{u_1}, \frac{u_M(u_2)}{u_2}, \ldots, \frac{u_M(u_n)}{u_n}\}$$

With: $u_M(u_n)$ is the membership function of M, taking values in$[0, 1]$, and $1 \leq i \leq n$.

Definition 2:

We have subset, $H_t, (t = 1, 2, ...)$ of real numbers be the universe of discourse by which we define a fuzzy sets $m_i(t)$are defined. If $M(t)$ is a collection of : $m_1(t), m_2(t), ...$ then, $M(t)$ is called a Fuzzy time series (FTS)defined on H_t.

Definition 3:

Suppose $M(t)$ is caused only by $M(t-1)$)and is denoted by $M(t-1) \rightarrow M(t)$; then there is a fuzzy relationship between $M(t)$ and $M(t-1)$ which can be expressed as the fuzzy relational equation:$M(t) = M(t-1) \circ R(t, t-1)$ where $\circ$ is Max–Min composition operator. The relation R is called the first-order of $M(t)$.

We will use in this study the heuristic fuzzy time approach, which well summarised by Wang (2011), we just add below the definition of heuristic function,

Definition 4:

In the heuristic models, heuristic function takes fuzzy logical relationship groups and relevant variables as parameters. All the fuzzy sets $m_1, m_2, ..m_k$ are well ordered. This condition greatly facilitates the selection of proper fuzzy sets by the heuristic function. We put Suppose $M(t-1) = m_i$ and the fuzzy logical relationship group for A_i is

$$m_i \rightarrow m_{i1}, m_{i2}, m_{i3}...$$

For following the application of our study,We highly recommend the paper of Qiang *et al* (1993) and Abbasov and Mamedova (2003). The performance and forecast accuracy to select the best method between the $ARIMA$ and FTS models is measured in terms of *Root Mean Square Errors* (RMSE); is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \tag{5}$$

With: $\hat{y}_i$: are predicted values, and y_i: observed values.

3. Empirical analysis and Discussion

We see from the plot blow, (2)- of the total cases detected over the study period, that all the three time series exhibit an exponential tendency of evolution, a pattern so dangerous for these countries.If we ranked them according to the speed of spread, the South Africa will be in the first place, it recorded the 150 cases in 14 days from the first confirmed cases in March the 6, with nearly 10 new cases per day. in the second place, we find Egypt, it recorded 210 confirmed cases in 33 days from the first detected positive cases of covid-19 in this country, as 6.36 cases per day, the last ranked country is Algeria, according to statistics, they are 90 confirmed cases over the period (2020-02-26/2020-03-19) , with a 3.91 cases per day as a rate evolution .
According to the statistics of health and demographic profile, the more populated country is Egypt with nearly 100 million inhabitants, followed by South Africa with

Indicators	Algeria	Egypt	South Africa
Total population (2016)	40,606,000	95,689,000	56,015,000
Gross national income per capita (PPP international $, 2013)	12,990	10,850	12,240
Life expectancy at birth m/f (years, 2016)	75/77	68/73	60/67
Probability of dying under five (per 1 000 live births, 2018)	24	21	34
Probability of dying between 15 and 60 years m/f (per 1 000 population, 2016)	106/84	205/121	359/246
Total expenditure on health per capita (Intl $, 2014)	932	594	1,148
Total expenditure on health as % of GDP (2014)	7.2	5.6	8.8

Table 1. Health and demographic profiles of the three countries, source: `https://www.who.int/countries/zaf/en/`

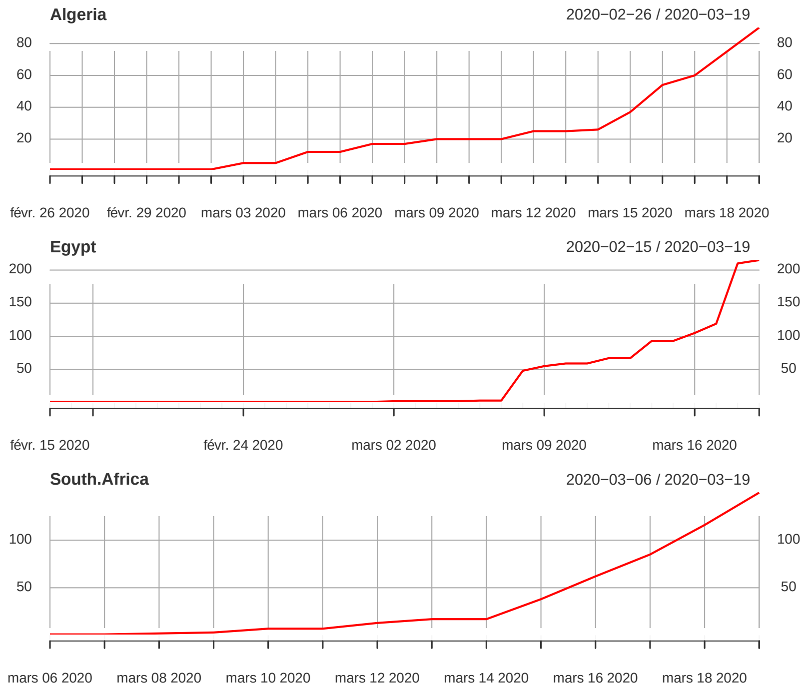
56 millions and Algeria with 40 millions, for health indicators, we reveal here a strange situation, when we look to the Total expenditure on health as % of GDP, the South Africa is in first place, then Algeria and Egypt, but ranking them according to the probability of dying (under five or between 15-60 years), the South Africa is in first rank, the same situation with the life expectancy at birth; we don't have a full response of this situation, but we think that a partial lighting on is studied by, Ataguba and McIntyre (2012) and Coovadia et *al* (2009). In other part, several critical deficiencies remain in the public health system in Egypt, fuelling concerns about its sustainability, El-Idrissi et *al* (2008)
In South Africa, about 9 percent of the population is 60 years or older, while the situation is complicated by the country's dual burden of HIV and tuberculosis. aljazeera (2020). For Algeria, and with the fall in oil prices, the situation is worsening further on the Algerian economy and the health system in particular, a scenario which could trigger a hyper spread of this virus, Mahfoud et *al* (2014). furthermore, the social health protection in Algeria suffer for a big constraints and obstacles, see Maeda and El Saharty (2008). Many other African countries face similar constraints.

Under this whole picture of health systems and economics conjectural, we will trying to give a predictable insight of covid-19 trend in these countries, by applying the two statical methods presented in section(2), the table below summarize the fitted ARIMA models for the time series data,

	Algeria		Egypt		South Africa
Optimal $ARIMA(p,d,q)$	$ARIMA(0,2,1)$	$MA(1) = -0.509$ $S.E = 0.159$	$ARIMA(0,2,1)$	$MA(1) = -0.826$ $S.E = 0.09$	$ARIMA(0,2,0)$
AIC	126.96		278.9		83.2
BIC	126.05		281.83		83.6
$Log\ likelihood$	−61.48		−137.45		−40.56

Table 2. Estimation results of $ARIMA$ fitted models on the three time series

Fig. 2. Trajectory of Covid-19 in Algeria, Egypt and South Africa over specific periods.



The analysis shows that the $MA(1)$ coefficients are significantly different from 0 for the covid-19 time series in Algeria and Egypt, where the optimal models are an $ARIMA(0, 2, 1)$, technically, this model is equivalent to a *linear exponential smoothing*: Linear exponential smoothing models are $ARIMA$models which use two non-seasonal differences in conjunction with MA terms, see Nau (2020) for more details about this point. For South Africa, the optimal $ARIMA$ model was an $ARIMA(0, 2, 0)$.

For Fuzzy time series modelling, as indicted in introduction, the only suitable R, package is *AnalyzeTS* implemented by Han (2016), We firstly decompose our universe of discourse , which simply represents the interval of data in each time series, with a heuristic approach we selected 12 membership function,For the fuzzy set of predicted values of the three series, see the appendix, (5), as you see in appendix, this is the same notation in definition 1 in the sub-section(2.2). After ARIMA estimation, we checked the presence of auto-correlation in residuals time series by applying the Ljung and Box (1978) test, we confirmed the hypothesis that the residuals from the ARIMA model have no autocorrelation. The same thing with ARCH test, there is no Heteroskedasticity in residuals variances.
According to our forecasting results,(see, Table(3) and Figure (3), the virus would begun spreading inside these countries with a high trend; Algeria, which had its

	ARIMA(p,d,q)							Fuzzy Time Series	
	Time	Point Forecast	Lo 8 0	Hi 8 0	Lo 95	Hi 95	RMSE	Point Forecast±SE	RMSE
Algeria	20-03-2020	103	97.48	109.27	94.36	112.39	4.2885	106(±16.28)	6.45
	21-03-2020	117	106.17	127.33	100.57	132.93		124(±17.45)	
	22-03-2020	130	114.37	145.88	106.03	154.22		143(±19.20)	
	23-03-2020	143	122.05	164.96	110.69	176.32		164(±21.20)	
	24-03-2020	157	129.22	184.96	114.58	199.18		186(±22.65)	
Egypt	20-03-2020	235	212.67	258.08	200.65	270.10	16.918	290(±75.44)	29.06
	21-03-2020	256	220.68	290.83	202.11	309.40		354(±64.23)	
	22-03-2020	276	229.48	322.80	204.79	347.49		426(±72.06)	
	23-03-2020	297	238.32	345.72	207.51	385.53		495(±68.63)	
	24-03-2020	316	246.94	386.86	209.91	423.89		565(±69.45)	
South Africa	20-03-2020	184	174.89	193.10	170.07	197.92	6.579	187 (±37.33)	9.05
	21-03-2020	218	197.63	238.36	186.58	249.14		227(±40.03)	
	22-03-2020	252	217.92	286.07	199.88	304.11		268(±41.18)	
	23-03-2020	286	236.11	335.88	209.71	362.28		310(±41.77)	
	24-03-2020	320	252.46	387.54	216.70	423.29		352(±42.24)	

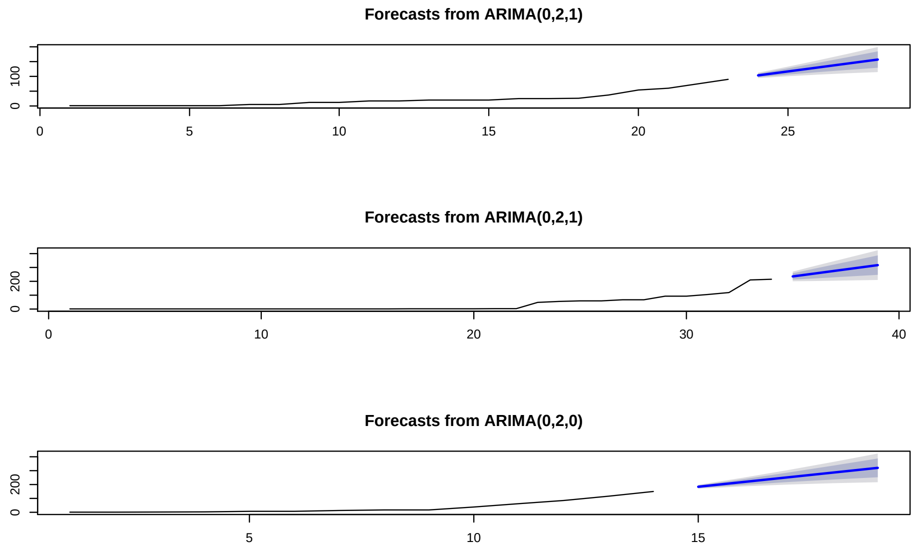
Table 3. Forecasting Results of the $ARIMA$ and FTS fitted models for Covid-19 trajectory in Algeria, Egypt and South Africa. LO, Hi is: lower and upper predictive intervals for a risk errors: $\alpha = 0.2, 0.05$

first case in 26-02-2020, it predicted to record 151 total cases, the same trend for South Africa, which announced its first case 12 days ago, now according to our forecasting in next five days,the number exceeds 320 cases, Egypt was not the exception of our forecasting, the number of total cases is likely to exceed 315 infected person. For the results of Fuzzy time series forecast, we see clearly the over-estimation of trajectory of Covid-19 compared to $ARIMA$ models, although the latter give better accuracy measures; we think that the predicted pattern of FTS stay a very likely trend of Corona Virus in theses countries.
The biggest concern was COVID-19 spreading in countries with weak health systems; the Governments of these countries would have to raise public health expenditure substantially to finance care at an adequate level, *but is it possible in this economic conjectural ?* But, we think that many other factors could make the *pandemic worse in Africa.* , we put here a quotation from,

> How do you protect the elderly, how can you tell village populations to wash their hands when there is no water, or use gel to sanitize their hands when they don't have enough money for food? "I'm afraid it will be chaos," *Francine Ntoumi*, University in the Republic of Congo.Science (2020)

As a last technical notes, We chosen just five (5) levels of forecasting, because the sample data is relatively small and the statistical methods used are more accurate for short prediction periods not long ones. of course, these models remain valid for new data (through a data update) for the next few days. The FTS forecasting plots have been presented in appendix.

Fig. 3. Forecasting plots of trajectory of Covid-19 in Algeria, Egypt and South Africa



4. Conclusion

In this study, we briefly and speedily as corona virus spread over world, studied the trend of this virus in three African countries : Algeria, Egypt and South Africa; theses countries have been already ranked the most risky regions for contamination. To check this hypothesis, we applied two statistical methods: Box-Jenkins and Fuzzy time series to forecast the trend of the incidence of this virus. The results, show a positive trend of contamination for all three countries, where the Fuzzy Time series outperforms the ARIMA models in term of forecasting. This finding are a serious ones for the governments of these countries to well prepare and manage all resources to deal with this virus. Despite, theses statistics and forecasting tools,we really have no certain idea (or *scenario*) how COVID-19 will behave in theses countries and in Africa in general.

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5. Appendix

Fig. 4. Output of Membership functions of the predicted Covid-19 data in South Africa

[1] " A[**2020-03-20**]

={(0.026811125136/u1),(0.114950550293/u2),(0.815769836410/u3),(0.067216592370/u4),(0.020139477118/u5),(0.009473719248/u6),(0.005477002912/u7),(0.003562102842/u8),(0.002499940661/u9),(0.001850443672/u10),(0.001424628503/u11),(0.001130468725/u12)}"

[2] "A[**2020-03-21**]

={(0.022354131990/u1),(0.081227266140/u2),(0.987347141039/u3),(0.092255237139/u4),(0.023928499124/u5),(0.010653274894/u6),(0.005985531995/u7),(0.003825610243/u8),(0.002653590599/u9),(0.001947705808/u10),(0.001490032637/u11),(0.001176535758/u12)}"

[3] "A[**2020-03-22**]

={(0.021092892526/u1),(0.073040808525/u2),(0.911063307912/u3),(0.103850134339/u4),(0.025454423502/u5),(0.011102778540/u6),(0.006173823261/u7),(0.003921478996/u8),(0.002708834402/u9),(0.001982380159/u10),(0.001513200966/u11),(0.001192773136/u12)}"

[4] "A[**2020-03-23**]

={(0.020398715803/u1),(0.068769980479/u2),(0.844050570501/u3),(0.111690689346/u4),(0.026422290489/u5),(0.011381048456/u6),(0.006288956086/u7),(0.003979664925/u8),(0.002742197980/u9),(0.002003247241/u10),(0.001527106817/u11),(0.001202498925/u12)}"

[5]

" A[**2020-03-24**]

={(0.019868733041/u1),(0.065617990268/u2),(0.784861199666/u3),(0.118574757065/u4),(0.027234683567/u5),(0.011610724006/u6),(0.006383182677/u7),(0.004027044852/u8),(0.002769274290/u9),(0.002020141523/u10),(0.001538345071/u11),(0.001210348090/u12)}"

Fig.5. Forecast plots of FTS models for the Corona virus.