Original Article

Application of Distribution-Delay Models to Estimating the Hospitalized Mortality Rate of Covid-19 According to Delay Effect of Hospitalizations Counts

Sedighe Rastaghi, Noushin Akbari Shark, Azadeh Saki*

Department of Biostatistics, School of Health, Mashhad University of Medical Sciences, Mashhad, Iran.

ARTICLE INFO   ABSTRACT

Introduction: The COVID-19 infectious epidemic has become a serious worry all over the world, including Iran. The high outbreak of disease ranked Iran as second in Asia and 11th in the world. Given the growing progress of this epidemic in infecting and killing individuals, it is essential to forecast the delay effect of the number of hospitalized upon the hospitalized mortality rate.

Methods: In this study, we used the daily Hospitalization cases of COVID-19 of IRAN for the period of 15-May 2020 to 5-Oct 2020 which were obtained from the online database. Five distribution delay models were compared for estimating and forecasting.

Results: Based on measurement errors DDM selected as the best model for forecasting the number of death. According to this model, the long-run effects show that observing the effect of hospitalization counts on death counts takes an average of five days and the long-run hospitalized mortality rate was 12%.

Conclusion: The overall hospitalized mortality rate of COVID-19 in Iran is less than the global rate of 15%. The mean of delay effect of daily hospitalization on mortality is approximately 5 days. Our findings showed distributed delay model (DDM) has better performance in the forecasting of the future behavior of the Coronavirus mortality, and providing to government and health care decision- makers the possibility to predict the outcomes of their decision on public health.

Introduction:

The coronavirus disease epidemic began in Wuhan, China, and gradually increased worldwide, affecting large numbers of people around the world. (1, 2). The World Health Organization announced the pandemic of a worldwide epidemic, On March 11, 2020. The *first* coronavirus *deaths* in IRAN were declared on Feb 19, 2020(3). Still, the full

Clinical symptoms of COVID-19 are not explicit and its exact risk of transmission is unknown. In general, everyone is at danger for this disease(4). The worst situation experienced by the USA followed by Brazil, India, Russia, and South Africa. The high outbreak of disease ranked Iran as second in Asia and 11th in the world. According to WHO, 320,117 Coronavirus Cases and

* . Corresponding Author Email: Sakia@mums.ac.ir

17,976 deaths in Iran, as of August 5, 2020 (5).

Due to the rapid transmission of this infection and the severity of its symptoms, the health care system is facing challenging problems and even developed countries have struggled to control it(6).

Managing worldwide epidemic such as coronavirus disease is crucial. without control with a high duplication rate (R0) measured at diverse immensity up to 6.5(7, 8) and up to 14.7% of those infected requiring hospitalization(9), the virus can pervade swiftly among a lot of people, Which leads to a high demand for hospital care and that the care system will not be able to handle it (6, 7). In such a situation, if patients do not have access to hospital services, it is likely to lead to inevitable deaths(10). Notwithstanding containment policy and quarantine attempts Around the World, the prevalence of this disease is increasing and many deaths have occurred in most countries. (11).

Increasing of confirming and hospitalization cases generate outnumbered of health care facilities and other medical supplies. Hospitals, quarantine sites, ventilators, beds, Personal Protective Equipment (PPE) kits, and other medical facilities need to strengthen the health system of those counties to overcome the negative consequences of COVID 19(12).

In this situation, statistical models that are deferent in nature are used for forecasting but do not insist on their correctness. The results of these models can be helpful for decision-making conditions for health policymakers and authorities(13). This study aimed to model and determine the epidemic trend and predict the number of patients hospitalized due to COVID-19 in Iran using mathematical and statistical modeling.

The review of the study was focused on modeling epidemics for various destinations. The researchers have used mathematical and statistical models for the aim. Konarasinghe (2020) has modeled the epidemic of the USA, UK, and Russia by utilizing ARIMA, Auto Regressive Distributed Delay Model (ADDM), and Double Exponential Smoothing (DES) (14).

Konarasinghe (2020) also used Auto-Regressive Integrated Moving Average (ARIMA) model, Autoregressive Distributed Delay Model (ADDM), Double Exponential Smoothing (DES) techniques, Liner trend model, Quadratic trend model, Growth Curve (GC) model, and Pearl-Reed Logistic model to forecast the number of infected cases within India and Brazil(15).

Soukhovolsky and et al (2020) used ADL(autoregressive distributed delay)-model on COVID-19 , allows describing non-monotonic changes about infection over time (16).

This study was conducted to the forecasting future of trend epidemic the number of daily death cases COVID-19 until 5 October 2020 in Iran using the autoregressive distributed delay (ARDD) and distributed delay (DD) models. In order to show the capability of the proposed models, a comparison was made between the ARDDM and DDM model. The total number of confirmed patients and deaths in Iran was 312035 and 17405, respectively, until 3 August 2020.

Given that the number of hospital mortality rate of COVID-19 varies on a daily basis and the estimation of mortality depends on the number of daily hospitalizations, the use of conventional methods to estimate hospital mortality rate is not appropriate. In this study, an attempt has been made to estimate this rate using distribution delay models and to obtain the delay effect of hospitalization cases in the future days. Therefore, finding predictive

models for forecasting mortality rate of COVID19 is a timely requirement. The study was designed to fill the knowledge gap. The objective of the study is to estimate Hospital mortality rate and forecast the number of deaths cases of COVID -19 in Iran.

Methodology

The daily Death and hospitalization cases of COVID-19 of Iran for the period of 15-May 2020 to 5-Oct 2020 were obtained from the ""https://github.com/smajidi/Iran-COVID-19-Data/blob/master/Iran_Dailly_Covid19_Stat.csv" database. Supported by the pattern recognition, Autoregressive Distributed Delay Model (ADDM), Distributed Delay Model, were tested to forecast the pandemic of Iran.

The forecasting ability of the models was assessed by Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Percentage Error (MPE), Symmetric Mean Absolute Percentage Error (SMAPE), Mean Absolute Percentage Error (MAPE), Mean Absolute Scaled Error (MASE), Mean Relative Absolute Error (MRAE), Geometric Mean Relative Absolute Error (GMRAE), Mean Bounded Relative Absolute Error (MBRAE) and Unscaled MBRAE (UMBRAE) which are measurements of errors. Dealing with delayed effects by defining temporal construction and explicit description of delays is feasible with the time series study design. Delayed effects are explained by distributed delay models (DDMs). These models are widely used in economics(17) and lately are used in studies of environmental factors to assess health effects(18-20).

In these methods, the effect of the explanatory variable on the dependent variable occurs over future period time at deferent delays. The assumption in common DDMs is linearity among dependent and independent variables(21).

Finite distributed delay models (DDM)

In this model we supposed that the effect explanatory variables may be delayed it means that its effect occurs overtime.

In a distributed delay model the effect of an exploratory variable x on y occurs over time not all at once. We can write the infinite linear DDM as follows:

$$Y_t = \alpha + \sum_{s=0}^{\infty} \beta_s X_{t-s} + \epsilon_t \qquad (1)$$

Were $E(\epsilon_t)=0$ and $var(\epsilon_t)= c$, α is the overall mean effect, β-parameters are called the delay weights and $\beta 0$ shows the effect of independent series. Estimate an infinite number of β coefficients is impossible, *and it is usually assumed that* $\lim_{i \to \infty} \beta_i = 0$ and $\sum_{i=0}^{\infty} \beta_i = \beta < \infty$.

Now assume that the changes *in* X_t *do not have* much effect after *a few periods of time* for example, *m,* which *means that all* β_i *after* β_m disappear. *In this case, the model reduces to a finite distributed delay, for which the upper limit of the summation signs in (1) is m.*

One solution is to bounded summation to finite-length q, so the DDM converts to be a finite linear DDM of order q. note that model parameters estimation is based on n-q pairs of $[y_t . x_t]$. The finite distributed delay model has two disadvantages which are related to the existence of multi-collinearity and decreasing degrees of freedom with increasing delay length *one important aspect to be considered is the number of parameters involved in these distributed delay models. In order to be parsimonious it is usually assumed that the coefficients of*

delayed variables are not all independent but functionally related.

DDMs are known as dynamic models because the effect of x on Y occurs over time. It means if the value of x changed today the effect of this change appears today and in the future days (22-24).

Autoregressive Distributed Delay Model (ARDDM)

The autoregressive DDMs are regressions that include delays of both the dependent and independent variables. An ARDD (p,q) model contains p delays of independent and q delays of dependent series. The model with y_t as dependent, x_{ti} as ith independent series, p_i and q are respectively as the delay order of ith independent series and as the autoregressive order of the model is define as follows(22):

$$Y_t = \mu_0 + \sum_{i=1}^{k} \beta_{0i} X_{ti} + \beta_{1i} X_{(t-1)i} + \cdots + \beta_{pi} X_{(t-p_i)i} + \gamma_1 Y_{t-1} + \cdots + \gamma_q Y_{t-q} + e_t \quad (2)$$

Among distributed delay models ARDD is more flexible and parsimonious(24).

Implement distributed delay models with Koyck transformation (koyckDDM)

This approach is the most general type of distributed delay model that knew as

geometric DDM in which the weights of the delayed declines in a geometric pattern $\beta_s = \beta \phi^s$. $\forall$s with $0 < \phi < 1$. The general form of this model defines as follows:

$$Y_t = \alpha + \beta(X_t + \phi X_{t-1} + \phi^2 X_{t-2} + \phi^3 X_{t-3} + \cdots) + \epsilon_t \quad (3)$$

This model has some restrictions to implement due to the infinite number of parameters and nonlinearity. One solution to deal with these restrictions is koyck transformation. After this transformation we

have finite DDM. In order to fit the model instrumental variables used. The geometric DDM with koyck transformation is as follows:

$$Y_t - \phi Y_{t-1} = \alpha(1 - \phi) + \beta X_t + (\epsilon_t - \phi \epsilon_{t-1}) \quad \rightarrow \quad Y_t = \gamma_1 + \gamma_2 Y_{t-1} + \gamma_3 X_t + v_t \quad (4)$$

where $\delta_1 = \alpha(1 - \varphi)$, $\delta_2 = \varphi$, $\delta_3 = \beta$ and $v_t = (\varepsilon_t - \phi \varepsilon_{t-1})$ shows the random error after the transformation. In this model, the first delay of the dependent series y_{t-1} is correlated with the error term and the error term v_t depends on both ε_t and ε_{t-1} . (22, 24)

Implement finite polynomial distributed lag model (polyDlm)

Finite distributed lag models, in general, suffer from the multi-collinearity due to the inclusion of the lags of the same variable in the model. To reduce the

impact of this multi-collinearity, a polynomial shape is imposed on the lag distribution (Judge and Griffiths, 2000). The resulting model is called the Polynomial Distributed Lag model or Almond Distributed Lag Model.

Imposing a polynomial pattern on the lag distribution is equivalent to representing β parameters with another kth order polynomial model of time. So, the effect of change in X_{t-s} on the expected value of Y_t is represented as follows:

$$\frac{\partial E(Y_t)}{\partial X_{t-s}} = \beta_s = \gamma_0 + \gamma_1 s + \gamma_2 s^2 + \cdots + \gamma_k s^k$$

where s = 0,...,q (Judge and Griffiths, 2000).
Then the model becomes (24):

$$Y_t = \alpha + \gamma_0 Z_{t0} + \gamma_1 Z_{t1} + \gamma_2 Z_{t2} + \cdots + \gamma_k Z_{tk} + \epsilon_t$$

Results:

We applied distributed-delay models to forecast the effect of hospitalization counts on the death count. All the models mentioned above were fitted to covid-19 data and better models for forecasting were selected Based on the error measurements.

Table1 shows the nine measurements of errors for fitted models. According to the value of these indexes ARDDM and DDM models had minimum errors and selected for forecasting the number of death.

Table 2 shows the results of fitting RDDM model. Base on this model the median delay 0.04, indicates that at the end of the fifth day at least half of the effect of hospitalizations number can be seen on the number of deaths. The long-run effect of the number of hospitalizations on the number of deaths is 0.09 and it takes an average of seventh days to observe the hospitalization counts on the death counts. It means if the number of hospitalizations at the beginning of the study was 1000 people, we will see 88 deaths by the end of the seventh day due to the long-run effect. Duo to the median delay, half of this number of the death will be observed in the first five days (43 people and approximately 8.8 people per day) and the other half of this number of deaths will occur on the sixth and seventh day (44 deaths on the sixth and seventh day, i.e. 22 deaths almost every day). Table 3 shows the results of fitting DDM model. Base on this model the median delay is 0.06, shows that at the end of the fifth day at least half of the effect of hospitalizations counts can be seen on the number of deaths. The long-run effect of the number of hospitalizations on the number of deaths is 0.12 and it takes an average of five days to observe the hospitalization counts on the death counts. It means if the number of hospitalizations at the beginning of the study was 1000 people, we will see 123 deaths by the end of the seventh day due to the long-run effect. Duo to the median delay, half of this number of the death will be observed in the first five days (60 people and approximately 12 people per day) and the other half of this number of deaths will occur on the sixth and seventh day (60 deaths on the sixth day and Seventh, which means 30 deaths almost every day).

Table 4 shows the forecasting number of death for different sets of hospitalization numbers on based ARDDM and DDM models. We define three trend scenarios for hospitalization counts: increasing, decreasing, and constant. In both ARDDM and DDM models predicted the death counts were almost identical and show an upward trend for both increasing and constant situations.

Table1: forecasting evaluation criteria, AIC and Adjusted R-squared for distributed delay models.

	n	MAE	MPE	MAPE	SMAPE	MASE	MSE	MRAE	GMRAE	MBRAE	UMBRAE	AIC	Adjusted R-squared
DDM	136	13.27	-0.01	0.10	0.10	0.88	259.98	1.92	0.95	0.55	1.24	1162.19	0.892
ARDD model	136	12.33	-0.01	0.09	0.09	0.82	234.19	1.51	0.85	0.57	1.34	1149.99	0.902
koyck model	142	13.64	-0.02	0.11	0.10	0.92	331.84	1.54	0.87	1.05	-22.32	1235.24	0.878
polyDDM model	136	13.32	-0.01	0.10	0.10	0.88	261.24	1.91	0.96	0.12	0.14	1152.85	0.895

Table2: results of fitting RDDM model

			Estimate	Std. Error	t value	Pr(>|t|)		Median $\frac{1}{2}\sum_{j=0}^{7}\alpha_j$	Long-run $\sum_{j=0}^{7}\alpha_j = \sum_{j=0}^{7}\beta_j + \alpha_{j-1}\gamma_1$	Instant effect $\beta_0 = \alpha_0$
Autoregressive distributed delay models		(Intercept)	4.234	4.400	0.962	0.338				
	β_0	hospitalize.t	0.009	0.008	1.178	0.241	α_0 0.0091			
	β_1	hospitalize .1	0.006	0.009	0.685	0.495	α_1 0.0083			
	β_2	hospitalize .2	-0.002	0.009	-0.255	0.799	α_2 -0.0022			
	β_3	hospitalize .3	0.009	0.009	1.016	0.312	α_3 0.0087	0.044138	0.0883	0.009108
	β_4	hospitalize .4	0.008	0.009	0.871	0.385	α_4 0.0075			
	β_5	hospitalize .5	0.020	0.009	2.231	0.027483 *	α_5 0.0195			
	β_6	hospitalize .6	0.018	0.009	1.996	0.048144 *	α_6 0.0185			
	β_7	hospitalize .7	0.019	0.009	2.180	0.031110 *	α_7 0.0189			
	γ_1	death.1	0.301	0.081	3.725	0.000294 ***				
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '										

Table3: results of fitting DDM model

		estimate	error	t-value	p-value	Median delay	Mean delay	Long-run
DDM	intercept	6.051963	4.589445	1.319	0.189652	0.061	4.653	0.123
	hospitalize.t	0.010990	0.008097	1.357	0.177068			
	hospitalize .1	0.008728	0.009094	0.960	0.338964			
	hospitalize .2	0.002667	0.008948	0.298	0.766193			
	hospitalize .3	0.010689	0.008973	1.191	0.235795			
	hospitalize .4	0.011352	0.008986	1.263	0.208796			
	hospitalize .5	0.021365	0.009182	2.327	0.021559 *			
	hospitalize .6	0.025504	0.009500	2.685	0.008228 **			
	hospitalize .7	0.031257	0.008398	3.722	0.000296 ***			
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '								

Table4: forecasting number of the death based on the different trend of hospitalization numbers

hospitalize	forecast.DDM	forecast.RDDM	hospitalize	forecast.DDM	forecast.RDDM	hospitalize	forecast.DDM	forecast.RDDM
1950	218.7	225.6	1950	218.7	225.6	1950	218.7	225.6
1950	210.4	214.0	2000	210.9	214.4	1900	209.8	213.5
1950	214.3	212.2	2050	215.9	213.6	1850	212.8	210.9
1950	205.2	206.9	2100	207.9	209.2	1800	202.6	204.7
1950	216.0	215.2	2150	220.3	218.8	1750	211.7	211.6
1950	230.5	227.9	2200	237.0	233.4	1700	224.0	222.4
1950	245.1	240.5	2250	254.9	249.0	1650	235.3	232.1
1950	245.0	244.3	2300	259.4	257.0	1600	230.6	231.5
1950	245.0	245.4	2350	265.5	263.7	1550	224.5	227.1
1950	245.0	245.7	2400	271.7	270.0	1500	218.4	221.5
1950	245.0	245.8	2450	277.8	276.2	1450	212.3	215.5
1950	245.0	245.9	2500	283.9	282.4	1400	206.1	209.4
1950	245.0	245.9	2550	290.0	288.5	1350	200.0	203.2
1950	245.0	245.9	2600	296.2	294.7	1300	193.9	197.1

Discussion:

According to the value of errors for fitted models ARDDM, and DDM models had minimum errors respectively. with fitted models we found that at the end of the fifth day of hospitalization, at least half of the effect of the hospitalization counts could be observed on the death counts.

Mathematical and statistical models provided by scientists can help significantly in identifying the course of the disease outbreak as well as identifying effective health interventions in reducing the progression of epidemic progression. There are three common approaches to such modeling. The first method is a nonlinear regression model such as the agent-based model (25).

These methods make it possible to accurately estimate based on given data as well as short-term predictions for incidence, but describing the mechanism of the pandemic is difficult to describe the based on them. SIR is the most common model used for coronaviruses spread such as SEIR-models (26-28).

Based on the SIR-model, by adopting that the entire population of the country should be in this group, then the outbreak will stop just if the Majority of people have been infected (29, 30). Furthermore, the SIR-models do not beg the question of the critical point of People infected, after reaching the early exponential phase. When choosing a model with large enough initial values, it is difficult to answer this question. Eventually, a recurrent bifurcation model was proposed, which showed that disease transmission is a pandemic even in a small number of cases. (31). This procedure is similar to the method we have proposed.

This paper investigates impact Number of hospitalizations and time delay Number of hospitalizations of COVID-19 pandemic (new cases and new deaths) on the IRAN Number of deaths. For this purpose, Autoregressive-Distribute Delay (ARDD) and Distribute Delay (DDM) model have been applied to the data from 15-May 2020 to 3-Aug 2020. In order to obtain short and long-term effects on the number of deaths From the outcome of the study based on DDM, hospitalizations have a long-run influence on new deaths. However, the relationship is not strong in the short-term. For controlling this dangerous state, the results of this study can be of great help to policymakers.

Based on forecasting results DDM was better than ARDD and also the overall estimate of death based on DDM was closer to a global standard that is 15 percent. For this purpose, Autoregressive-Distribute Delay (ARDD) and Distribute Delay (DDM) model have been applied to the data from 15-May 2020 to 3-Aug 2020 in order to capture both long-run and short-run impact on a number of deaths.

Conclusion

From a data point of view, this model is very simple and practical for calculations, so only data from the current rate is sufficient to confirm the proposed model. However, the coefficient of determination of the R2 model is very high. Given this, we predict hospital mortality for up to 14 days.

The ADL model allows describing non-monotonic changes about infection over time, and assists governments and health policy makers in anticipating and making appropriate health decisions.

Author contributions

AS Have made substantial contributions to conception and design; SR and NA contributed in statistical analysis and wrote the

manuscript; AS critically reviewed the manuscript.

Competing Interests

There is no competing interest.

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