

# Employing ARIMA Model Projections to Inform Neonatal Healthcare Policies and Resource Allocation in the Syrian Republic

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**Abstract** - The Syrian crisis has caused serious damage to health infrastructure and triggered exodus of thousands of qualified and experienced healthcare workers leaving the health system at the verge of collapsing. The negative impacts of this war will remain a huge contributing factor to neonatal mortality even in future. This study uses annual time series data on neonatal mortality rate (NMR) for Syria from 1960 to 2019 to predict future trends of NMR over the period 2020 to 2030. Unit root tests have shown that the series under consideration is an I (1) variable. The optimal model based on AIC is the ARIMA (2,1,1) model. The ARIMA model projections indicate that neonatal mortality will decline slightly and hover around 10 deaths per 1000 live births throughout the forecast period. Therefore, we encourage Syrian authorities to attend to various factors which significantly contribute to neonatal mortality across the country such as destroyed infrastructure and shortage of skilled healthcare workers.

**Keywords:** ARIMA, Forecasting, NMR.

## I. INTRODUCTION

The Syrian war is a cause for concern in recent times and regarded by the United Nations High Commission as the ‘worst humanitarian crisis of our time’ (UNHCR, 2015). Persistence of this war poses a global security and health threat. The massive displacements of Syrians and death of civilians calls for all parties involved to consider seriously the immediate and long term health consequences that will affect the Syrian people especially the health and safety of women and children who are the future of this beloved country (Devakumar *et al.* 2015; Bhutta *et al.* 2010). The Syrian crisis has led to the destruction of health infrastructure and massive exodus of trained health professionals (Dejong *et al.* 2017). Shortage of medical staff will negatively impact on the smooth delivery of maternal and child health services making it difficult to achieve set sustainable development goals by 2030. The aim of this paper is to project future trends of neonatal mortality rate for Syria using the widely applied Box-Jenkins ARIMA approach. The ARIMA (p, d, q) model is useful in modelling linear data and easy to apply (Nyoni, 2018; Box-Jenkins, 1970). The findings of this study are expected to guide neonatal policy and implementation of appropriate intervention strategies to curb neonatal mortality.

## II. LITERATURE REVIEW

A multisite retrospective Kenyan cohort study was carried by Irimu *et al.* (2021) to find out the proportion of all admissions and deaths in the neonatal age group and examine morbidity and mortality patterns, stratified by birth weight, and their variation across hospitals. Intrapartum related complications was the single most common diagnosis among the neonates with birth weight of 2000 g or more who died. A threefold variation in mortality across hospitals was observed for birth weight categories 1000– 1499 g and 1500–1999g. Dejong *et al.* (2017) utilized Countdown to 2015 (Millennium Development Goals) health indicators to provide an up-to-date review and analysis of the best available data on Syrian refugees in Jordan, Lebanon and Turkey and internally displaced within Syria and explored data challenges in this conflict setting. The study obtained data from electronic databases and relevant stakeholders. The results indicated that in Syria, the infant mortality rate and under-five mortality rate increased, and coverage of antenatal care (one visit with a skilled attendant), skilled birth attendance and vaccination (except for DTP3 vaccine) declined. The number of Syrian refugee women attending more than four antenatal care visits was low in Lebanon and in non-camp settings in Jordan. In another study Machio (2017) investigated the effects of antenatal and skilled delivery care services on neonatal and under-five mortality in Kenya using pooled Kenya demographic and health survey data for 1998, 2003, 2008/2009 and 2014. Two-stage residual inclusion estimation procedure and the control function

approach were used to test and control for potential endogeneity of antenatal and skilled delivery care and for potential unobserved heterogeneity. Findings revealed that adequate use of antenatal care services reduced risk of neonatal and under-five mortality by 2.4 and 4.2 percentage points respectively Devakumar *et al.*(2015)outlined the effects of the war on Syria’s children, highlighting the less documented longer-term effects. The study highlighted long term effects such as physical disability, mental trauma, and intergeneration effects like increases in rates of preterm birth, fetal growth restriction, and maternal infections leading to congenital abnormalities.

### III. METHODOLOGY

#### The Autoregressive (AR) Model

A process  $S_t$  (NMR at time t) is an autoregressive process of order p, that is, AR (p) if it is a weighted sum of the past p values plus a random shock ( $Z_t$ ) such that:

$$S_t = \phi_1 S_{t-1} + \phi_2 S_{t-2} + \phi_3 S_{t-3} + \dots + \phi_p S_{t-p} + Z_t \dots \dots \dots [1]$$

Using the backward shift operator, B, such that  $BS_t = S_{t-1}$ , the AR (p) model can be expressed as in equation [2] below:

$$Z_t = \phi(B)S_t \dots \dots \dots [2]$$

where  $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \phi_3 B^3 - \dots - \phi_p B^p$

The 1<sup>st</sup> order AR (p) process, AR (1) may be expressed as shown below:

$$S_t = \phi S_{t-1} + Z_t \dots \dots \dots [3]$$

Given  $\phi = 1$ , then equation [3] becomes a random walk model. When  $|\phi| > 1$ , then the series is referred to as explosive, and thus non-stationary. Generally, most time series are explosive. In the case where  $|\phi| < 1$ , the series is said to be stationary and therefore its ACF (autocorrelation function) decreases exponentially.

#### The Moving Average (MA) Model

A process is referred to as a moving average process of order q, MA (q) if it is a weighted sum of the last random shocks, that is:

$$S_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \dots + \theta_q Z_{t-q} \dots \dots \dots [4]$$

Using the backward shift operator, B, equation [4] can be expressed as follows:

$$S_t = \theta(B)Z_t \dots \dots \dots [5]$$

where  $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$

Equation [4] can also be expressed as follows:

$$S_t - \sum_{j=1}^q \pi_j S_{t-j} = Z_t \dots \dots \dots [6]$$

for some constant  $\pi_j$  such that:

$$\sum_{j=1}^q |\pi_j| < \infty$$

This implies that it is possible to invert the function taking the  $Z_t$  sequence to the  $S_t$  sequence and recover  $Z_t$  from present and past values of  $S_t$  by a convergent sum.

#### The Autoregressive Moving Average (ARMA) Model

While the above models are good, a more parsimonious model is the ARMA model. The AR, MA and ARMA models are applied on stationary time series only. The ARMA model is just a mixture of AR (p) and MA (q) terms, hence the name ARMA (p, q). This can be expressed as follows:

$$\phi(B)S_t = \theta(B)Z_t \dots \dots \dots [7]$$

Thus:

$$S_t(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) = Z_t(1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q) \dots \dots \dots [8]$$

where  $\phi(B)$  and  $\theta(B)$  are polynomials in B of finite order p, q respectively.

**The Autoregressive Integrated Moving Average (ARIMA) Model**

The AR, MA and ARMA processes are usually not applied empirically because in most cases many time series data are not stationary; hence the need for differencing until stationarity is achieved.

<p>The first difference is given by:  <math>S_t - S_{t-1} = S_t - BS_t</math></p> <p>The second difference is given by:  <math>S_t(1 - B) - S_{t-1}(1 - B) = S_t(1 - B) - BS_t(1 - B) = S_t(1 - B)(1 - B) = S_t(1 - B)^2</math></p> <p>The third difference is given by:  <math>S_t(1 - B)^2 - S_{t-1}(1 - B)^2 = S_t(1 - B)^2 - BS_t(1 - B)^2 = S_t(1 - B)^2(1 - B) = S_t(1 - B)^3</math></p> <p>The d<sup>th</sup> difference is given by:  <math>S_t(1 - B)^d</math></p>	}	... [9]
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Given the basic algebraic manipulations above, it can be inferred that when the actual data series is differenced “d” times before fitting an ARMA (p, q) process, then the model for the actual undifferenced series is called an ARIMA (p, d, q) model. Thus equation [7] is now generalized as follows:

$$\phi(B)(1 - B)^d S_t = \theta(B)Z_t \dots \dots \dots [10]$$

Therefore, in the case of modeling and forecasting NMR, equation [10] can be written as follows:

$$\phi(B)(1 - B)^d S_t = \theta(B)Z_t \dots \dots \dots [11]$$

**The Box – Jenkins Approach**

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018). The Box – Jenkins technique was proposed by Box & Jenkins (1970) and is widely used in many forecasting contexts, including human health. In this paper, hinged on this technique; the researcher will use automatic ARIMA modeling for estimating equation [10].

**Data Issues**

This study is based on annual NMR in Syria for the period 1960 to 2019. The out-of-sample forecast covers the period 2020 to 2030. All the data employed in this research paper was gathered from the World Bank online database.

**Evaluation of ARIMA Models**

Criteria Table

Table 2: Criteria Table

Model Selection Criteria Table

Dependent Variable: DLOG(S)

Date: 01/29/22 Time: 11:39

Sample: 1960 2019

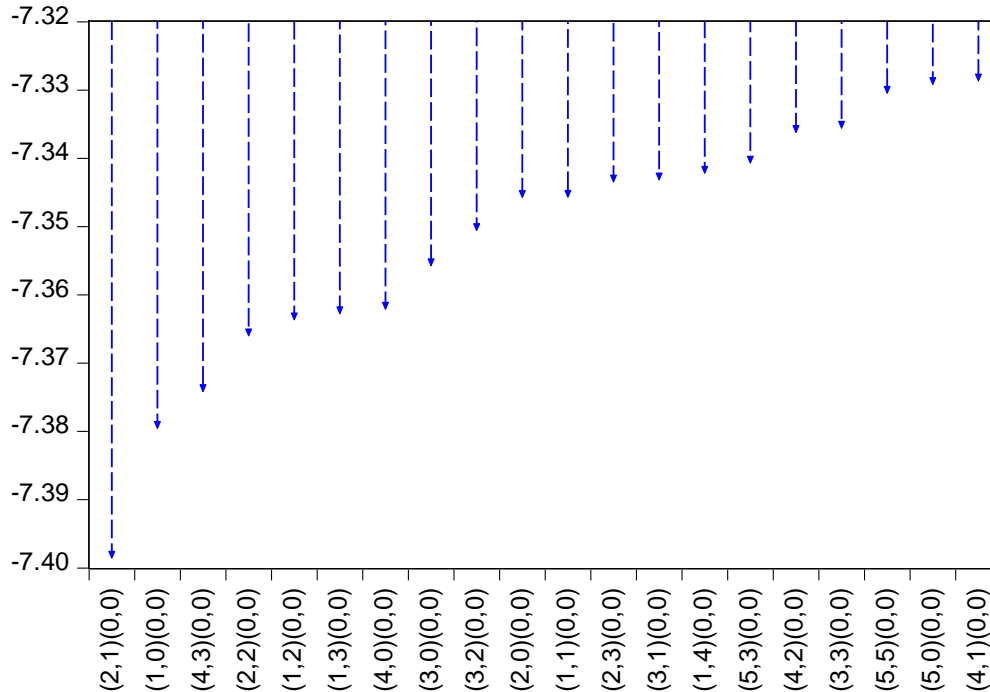
Included observations: 59

Model	LogL	AIC*	BIC	HQ
(2,1)(0,0)	223.241248	-7.398008	-7.221946	-7.329281
(1,0)(0,0)	220.679399	-7.378963	-7.273325	-7.337726
(4,3)(0,0)	226.520460	-7.373575	-7.056662	-7.249865
(2,2)(0,0)	223.280106	-7.365427	-7.154152	-7.282954
(1,2)(0,0)	222.211189	-7.363091	-7.187029	-7.294363
(1,3)(0,0)	223.184717	-7.362194	-7.150919	-7.279721
(4,0)(0,0)	223.165260	-7.361534	-7.150259	-7.279061
(3,0)(0,0)	221.977627	-7.355174	-7.179111	-7.286446
(3,2)(0,0)	223.824898	-7.349997	-7.103509	-7.253778
(2,0)(0,0)	220.681867	-7.345148	-7.204298	-7.290166
(1,1)(0,0)	220.681075	-7.345121	-7.204271	-7.290139
(2,3)(0,0)	223.614954	-7.342880	-7.096392	-7.246661
(3,1)(0,0)	222.606692	-7.342600	-7.131325	-7.260127
(1,4)(0,0)	223.577881	-7.341623	-7.095136	-7.245404
(5,3)(0,0)	226.533279	-7.340111	-6.987986	-7.202656
(4,2)(0,0)	224.400944	-7.335625	-7.053925	-7.225661
(3,3)(0,0)	224.382316	-7.334994	-7.053294	-7.225030
(5,5)(0,0)	228.232496	-7.329915	-6.907365	-7.164969
(5,0)(0,0)	223.193756	-7.328602	-7.082114	-7.232383
(4,1)(0,0)	223.179401	-7.328115	-7.081628	-7.231897
(2,5)(0,0)	224.864995	-7.317457	-7.000545	-7.193748
(1,5)(0,0)	223.773779	-7.314365	-7.032665	-7.204401
(5,4)(0,0)	226.712246	-7.312280	-6.924942	-7.161079
(2,4)(0,0)	223.654679	-7.310328	-7.028628	-7.200364
(3,4)(0,0)	224.552875	-7.306877	-6.989965	-7.183167
(5,2)(0,0)	224.482825	-7.304503	-6.987590	-7.180793
(5,1)(0,0)	223.286598	-7.297851	-7.016151	-7.187887
(3,5)(0,0)	224.722418	-7.278726	-6.926601	-7.141271
(4,5)(0,0)	225.140590	-7.259003	-6.871666	-7.107802
(0,5)(0,0)	220.370609	-7.232902	-6.986415	-7.136683
(0,4)(0,0)	216.275734	-7.127991	-6.916716	-7.045518
(0,3)(0,0)	214.739647	-7.109819	-6.933756	-7.041091
(4,4)(0,0)	212.331661	-6.858700	-6.506575	-6.721245
(0,2)(0,0)	203.903519	-6.776390	-6.635540	-6.721408
(0,1)(0,0)	192.701131	-6.430547	-6.324909	-6.389310
(0,0)(0,0)	168.677823	-5.650096	-5.579671	-5.622605

Criteria Graph

Figure 1: Criteria Graph

Akaike Information Criteria (top 20 models)



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

Forecast Comparison Graph

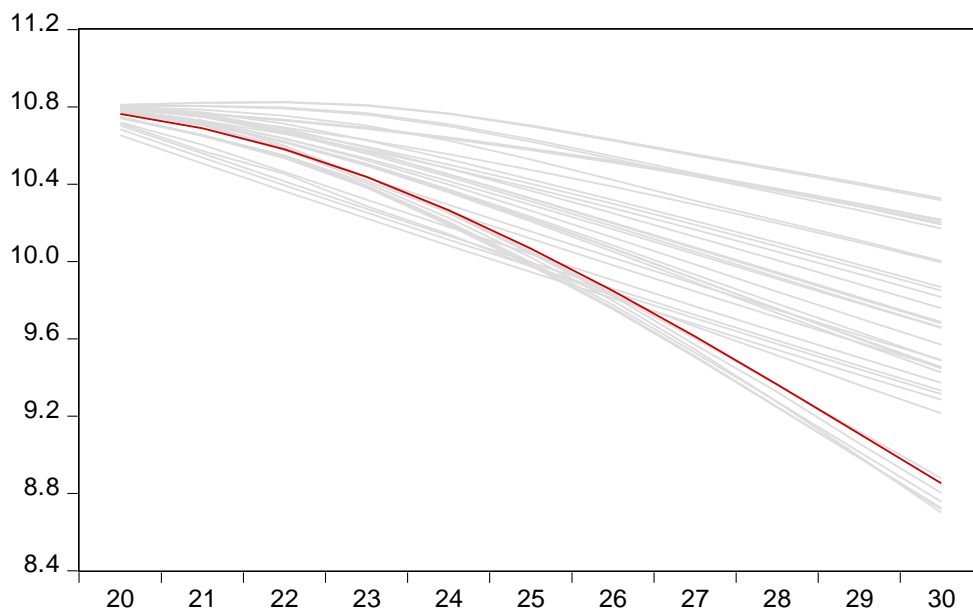


Table 2 and Figure 1 indicate that the optimal model is the ARIMA (2,1,1) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (2,1,1) model.

#### IV. RESULTS

##### Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting	
Selected dependent variable: DLOG(S)	
Date: 01/29/22 Time: 11:39	
Sample: 1960 2019	
Included observations: 59	
Forecast length: 11	
<hr/>	
Number of estimated ARMA models: 36	
Number of non-converged estimations: 0	
Selected ARMA model: (2,1)(0,0)	
AIC value: -7.39800841655	

##### Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: DLOG(S)				
Method: ARMA Maximum Likelihood (BFGS)				
Date: 01/29/22 Time: 11:39				
Sample: 1961 2019				
Included observations: 59				
Convergence achieved after 64 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.016493	0.002218	-7.436817	0.0000
AR(1)	1.897237	0.071635	26.48489	0.0000
AR(2)	-0.920703	0.065232	-14.11430	0.0000
MA(1)	-0.999999	1950.182	-0.000513	0.9996
SIGMASQ	2.82E-05	0.001414	0.019958	0.9842
R-squared	0.853380	Mean dependent var		-0.013745
Adjusted R-squared	0.842519	S.D. dependent var		0.013991
S.E. of regression	0.005552	Akaike info criterion		-7.398008
Sum squared resid	0.001665	Schwarz criterion		-7.221946
Log likelihood	223.2412	Hannan-Quinn criter.		-7.329281
F-statistic	78.57457	Durbin-Watson stat		2.199406
Prob(F-statistic)	0.000000			
Inverted AR Roots	.95-.14i	.95+.14i		
Inverted MA Roots	1.00			

## ARIMA () Model Forecast

### Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	10.76313623446382
2021	10.68940456274774
2022	10.58007470446712
2023	10.43754835841294
2024	10.26516614342597
2025	10.06698107890979
2026	9.847517737060846
2027	9.611535264356315
2028	9.363809656332701
2029	9.108946653844881
2030	8.851232138863395

Table 5 clearly indicates that neonatal mortality will decline slightly and hover around 10 deaths per 1000 live births throughout the forecast period.

## V. POLICY IMPLICATION & CONCLUSION

The Syrian political crisis is the major setback for the country to achieve all its sustainable development goal targets by the end of 2030 including SDG-3 targets 3.1 and 3.2 which aim to reduce maternal mortality to less than 70 maternal deaths per 100 000 live births and neonatal mortality to at least 12 deaths per 1000 live births by 2030. The country's infrastructure is continuously being destroyed and health care professionals are fleeing the country leaving the health system in a critical state. This paper projects NMR for Syria and the findings indicate that neonatal mortality will decline slightly and hover around 10 deaths per 1000 live births throughout the forecast period. Therefore, we encourage Syrian authorities to attend to various factors that significantly contribute to neonatal mortality across the country such as destroyed infrastructure and shortage of skilled healthcare workers.

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