Addressing Adverse Neonatal Health Outcomes in Jordan Using Scientific Evidence Generated by the ARIMA Model

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Abstract - **This study uses annual time series data on neonatal mortality rate (NMR) for Jordan 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 (I) variable. The optimal model based on AIC is the ARIMA (2,1,2) model. The findings of study indicate that neonatal mortality will slightly decrease from around 9 in 2020 to 7 deaths per 1000 live births by the end of 2030.Therefore, policy makers in Jordan should craft country specific neonatal policies to keep neonatal deaths under control by ensuring availability of trained medical staff &medical supplies, and strengthening the referral system.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

Jordan has a total fertility rate of 3.5 births per woman with a birth rate of 27 per 1000 people (Jordan, 2012). The country's neonatal mortality rate (NMR) significantly declined during the period 1990- 2013 but still remains high (UNICEF, 2014). Neonatal mortality in Jordan contributes 50% of all under 5 deaths with prematurity accounting for half of neonatal deaths and neonatal mortality rate is around 14 per 1000 live births (Khasawneh & Khriesat, 2020). The aim of this paper is to model and project future trends of neonatal mortality rate (NMR) for Jordan using the popular Box-Jenkins ARIMA model. Linear time series data can be successfully analyzed using this model (Nyoni, 2018; Box & Jenkins, 1970). Forecast results are expected to guide policy formulation, decision making and allocation of resources to the maternal and child health program with the aim of effectively controlling the problem of neonatal mortality in the country. The findings will assist in tracking progress towards achieving the set sustainable development goal 3 target 3.2 which aims to reduce neonatal mortality to at least 12 neonatal deaths per 1000 live births by 2030.

II. LITERATURE REVIEW

Khader*et al* (2021) explored the healthcare professionals' perception about the usability of JSANDS.A descriptive qualitative approach, using focus group discussions, was adopted. A total of 5 focus groups including 23 focal points were conducted in five participating hospitals in Jordan. The study findings revealed that JSANDS was perceived positively by the current users. According to them, it provides a formative and comprehensive data on stillbirths and neonatal deaths and their causes. Khasawneh & Khriesat (2020) assessed the rate of prematurity and determine the mortality rate and short-term outcomes among premature infants admitted at King Abdullah University Hospital (KAUH) in Jordan. A retrospective cross-sectional review of all premature infants admitted at KAUH between August 2016 and August 2018 was conducted. A high rate of prematurity was observed, the majority were late preterm with reassuring outcomes. In a 2019 study, Souza *et al* examined the determinants of neonatal mortality in Foz do Iguassuin Brazil. The authors analyzed all neonatal deaths that occurred in Foz do Iguassu from 2012 to 2016. Birth and mortality data were extracted from two national governmental databases (SINASC and SIM). It was found that high rate of neonatal death in Foz do Iguassu is strongly associated with newborn characteristics and not associated with maternal socio-demographic characteristics. A cross sectional study was conducted by Nadin *et al.* (2017) to investigate the incidence of preterm delivery, maternal risk factors for having a preterm neonate, and preterm neonates' mortality in Jordan. Socio-demographic, perinatal, delivery risk factors, and survival information were gathered in pre- and post-hospital discharge interviews with 21075 women who gave birth to live neonates at ≥20 weeks of gestation in 18 hospitals in Jordan. Women were interviewed between 2012 and 2013. The study revealed that mortality rate was considerably higher among preterm neonates than among term neonates; discrepancies between Jordan and other countries existed.

III. METHODOLOGY

The Autoregressive (AR) Model

A process J_t (annual 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:

$$J_t = \emptyset_1 J_{t-1} + \emptyset_2 J_{t-2} + \emptyset_3 J_{t-3} + \cdots + \emptyset_p J_{t-p} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

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

$$Z_t = \emptyset(B)J_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

where $\emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \emptyset_3 B^3 - \cdots - \emptyset_p B^p$

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

$$J_t = \emptyset J_{t-1} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

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

The Moving Average (MA) Model

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

$$J_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \cdots + \theta_q Z_{t-q} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [4]$$

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

$$J_t = \theta(B)Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [5]$$

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

Equation [4] can also be expressed as follows:

$$J_t - \sum_{i \leq 1} \pi_j J_{t-i} = Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [6]$$

for some constant π_i such that:

$$\sum_{i \leq 1} |\pi_i| < \infty$$

This implies that it is possible to invert the function taking the Z_t sequence to the J_t sequence and recover Z_t from present and past values of J_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:

$$\emptyset(B)J_t = \theta(B)Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [7]$$

Thus:

$$J_t\left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) = Z_t\left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right) \ldots \ldots \ldots \ldots \ldots \ldots [8]$$

where$\emptyset(B)$ 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.

$$\left.\begin{array}{c} The\ first\ difference\ is\ given\ by: \\ J_t - J_{t-1} = J_t - BJ_t \\ The\ second\ difference\ is\ given\ by: \\ J_t(1 - B) - J_{t-1}(1 - B) = J_t(1 - B) - BJ_t(1 - B) = J_t(1 - B)(1 - B) = J_t(1 - B)^2 \\ The\ third\ difference\ is\ given\ by: \\ J_t(1 - B)^2 - J_{t-1}(1 - B)^2 = J_t(1 - B)^2 - BJ_t(1 - B)^2 = J_t(1 - B)^2(1 - B) = J_t(1 - B)^3 \\ The\ d^{th}\ difference\ is\ given\ by: \\ J_t(1 - B)^d \end{array}\right\} \ldots [9]$$

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:

$$\emptyset(B)(1 - B)^d J_t = \theta(B) Z_t \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots [10]$$

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

$$\emptyset(B)(1 - B)^d J_t = \theta(B) Z_t \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots [11]$$

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 health sector. 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 Jordan 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(J)
Date: 01/23/22   Time: 09:41
Sample: 1960 2019
Included observations: 59

Model	LogL	AIC*	BIC	HQ
(2,2)(0,0)	240.511013	-7.949526	-7.738251	-7.867053
(4,4)(0,0)	244.249138	-7.940649	-7.588524	-7.803193
(4,5)(0,0)	244.908416	-7.929099	-7.541761	-7.777898
(3,2)(0,0)	240.782881	-7.924843	-7.678356	-7.828625
(0,5)(0,0)	240.592766	-7.918399	-7.671911	-7.822180
(5,4)(0,0)	244.465262	-7.914077	-7.526739	-7.762876
(5,5)(0,0)	245.217397	-7.905674	-7.483124	-7.740728
(2,4)(0,0)	240.867899	-7.893827	-7.612127	-7.783863
(4,0)(0,0)	238.852007	-7.893288	-7.682013	-7.810815
(3,3)(0,0)	240.844225	-7.893025	-7.611325	-7.783060
(2,5)(0,0)	241.807929	-7.891794	-7.574882	-7.768084
(4,3)(0,0)	241.718988	-7.888779	-7.571867	-7.765069
(1,5)(0,0)	240.703843	-7.888266	-7.606566	-7.778302
(4,1)(0,0)	239.562432	-7.883472	-7.636985	-7.787254
(1,4)(0,0)	239.551940	-7.883117	-7.636629	-7.786898
(3,4)(0,0)	241.472351	-7.880419	-7.563506	-7.756709
(5,0)(0,0)	239.293148	-7.874344	-7.627857	-7.778125
(1,3)(0,0)	238.131791	-7.868874	-7.657599	-7.786401
(1,2)(0,0)	236.984775	-7.863891	-7.687828	-7.795163
(5,3)(0,0)	241.828977	-7.858609	-7.506484	-7.721154
(4,2)(0,0)	239.591578	-7.850562	-7.568862	-7.740598
(5,1)(0,0)	239.567812	-7.849756	-7.568056	-7.739792
(3,5)(0,0)	241.538897	-7.848776	-7.496651	-7.711321
(2,3)(0,0)	238.410509	-7.844424	-7.597937	-7.748205
(5,2)(0,0)	239.880097	-7.826444	-7.509531	-7.702734
(0,4)(0,0)	235.899412	-7.793200	-7.581925	-7.710727
(0,3)(0,0)	234.710991	-7.786813	-7.610751	-7.718086
(3,1)(0,0)	235.597745	-7.782974	-7.571699	-7.700501
(2,0)(0,0)	232.491457	-7.745473	-7.604623	-7.690491
(3,0)(0,0)	232.818359	-7.722656	-7.546594	-7.653929
(2,1)(0,0)	232.596935	-7.715150	-7.539088	-7.646423
(1,1)(0,0)	230.366616	-7.673445	-7.532595	-7.618462
(1,0)(0,0)	227.827291	-7.621264	-7.515627	-7.580028
(0,2)(0,0)	227.715949	-7.583591	-7.442741	-7.528609
(0,1)(0,0)	219.798573	-7.349104	-7.243467	-7.307868
(0,0)(0,0)	211.422493	-7.099068	-7.028643	-7.071577

Criteria Graph

Figure 1: Criteria Graph
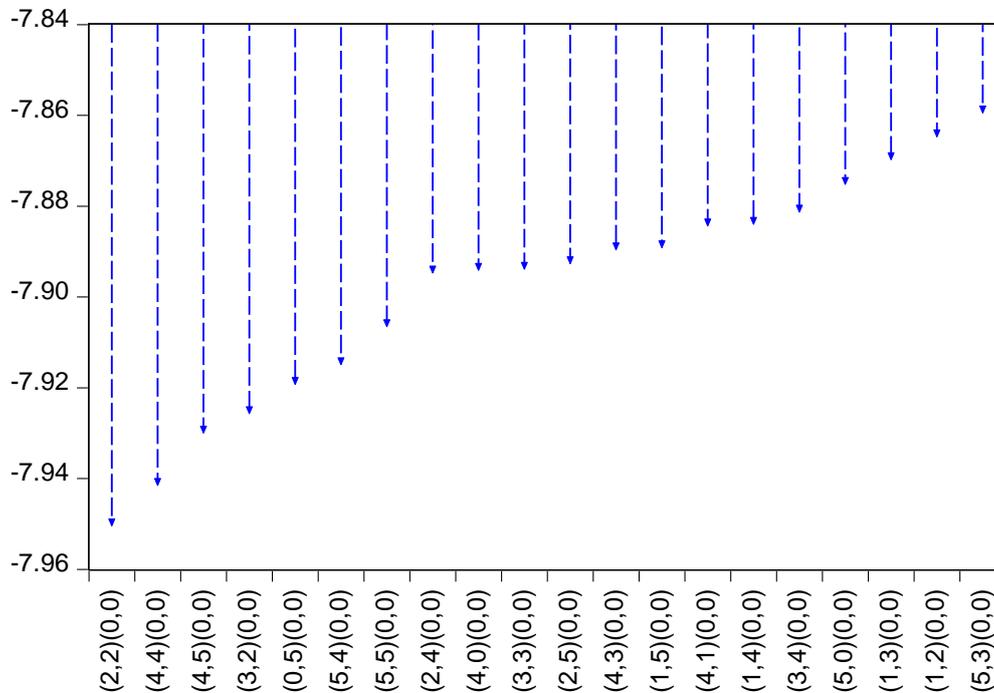
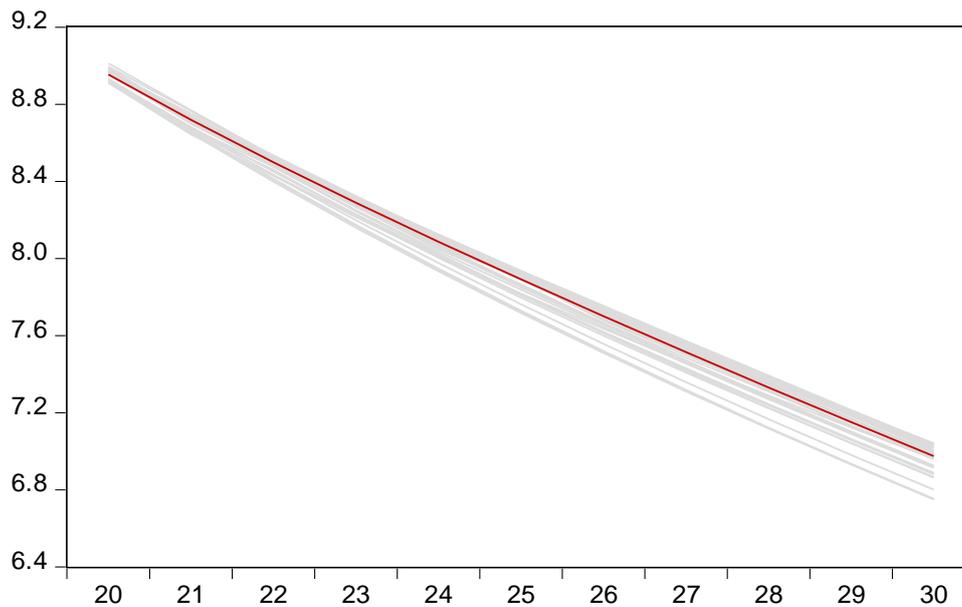**Forecast Comparison Graph**

Figure 2: Forecast Comparison Graph

Table 2 and Figure 1 indicate that the optimal model is the ARIMA (2,1,2) 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 (2,1,2) model.

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(J)
Date: 01/23/22   Time: 09:41
Sample: 1960 2019
Included observations: 59
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (2,2)(0,0)
AIC value: -7.94952585959

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: DLOG(J)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/22   Time: 09:41
Sample: 1961 2019
Included observations: 59
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.024922	0.002190	-11.37887	0.0000
AR(1)	1.380785	0.129406	10.67015	0.0000
AR(2)	-0.591930	0.150239	-3.939919	0.0002
MA(1)	-1.108301	0.108164	-10.24648	0.0000
MA(2)	0.854147	0.090524	9.435605	0.0000
SIGMASQ	1.61E-05	2.45E-06	6.545853	0.0000

R-squared	0.644730	Mean dependent var	-0.025036
Adjusted R-squared	0.611214	S.D. dependent var	0.006780
S.E. of regression	0.004227	Akaike info criterion	-7.949526
Sum squared resid	0.000947	Schwarz criterion	-7.738251
Log likelihood	240.5110	Hannan-Quinn criter.	-7.867053
F-statistic	19.23646	Durbin-Watson stat	2.058097
Prob(F-statistic)	0.000000		

Inverted AR Roots	.69-.34i	.69+.34i

Inverted MA Roots	.55+.74i	.55-.74i

ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	8.953239185147174
2021	8.719753249919523
2022	8.498890809528994
2023	8.288677367362598
2024	8.086792557902419
2025	7.891192432173816
2026	7.700401959998143
2027	7.513559401522042
2028	7.330310344295562
2029	7.150638983936591
2030	6.974700161817864

Table 2 clearly indicates that neonatal mortality will slightly decrease from around 9 in 2020 to 7 deaths per 1000 live births by the end of 2030.

V. POLICY IMPLICATION & CONCLUSION

Neonatal mortality remains a public health problem not only in Jordan but across the whole world. Several previous studies in Jordan have indicated that prematurity among other causes remains a challenge in the reduction of neonatal mortality and improvement of neonatal health outcomes. Previous studies done in African and Asian countries highlighted the importance of improving the quality of healthcare services during antenatal care, delivery and postnatal periods so as to effectively deal with the problem of mortality in neonates. In this study we apply the ARIMA model to predict future trends of NMR Jordan and the findings suggest that neonatal mortality will slightly decrease from around 9 in 2020 to 7 deaths per 1000 live births by the end of 2030. Therefore policy makers in Jordan should craft country specific neonatal policies to keep neonatal deaths under control by ensuring availability of trained medical staff & medical supplies, and strengthening the referral system.

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