Enhancing Demographic Forecasts: An Application of Adaptive Linear Neuron (Adaline) and ARIMA Models to Iraqi Fertility Rates Data

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ABSTRACT

The projection of fertility rates has tremendous implications for how we manage resources, develop policy, and plan demographic groups, especially in countries experiencing social and economic change like Iraq. The purpose of this study was to advance demographic forecasting by analysing the predictive accuracy of two time-series models, namely an Autoregressive Integrated Moving Average (ARIMA) model and an Adaptive Linear Neuron (Adaline) Artificial Neural Network. An analysis of annual fertility rate data from 1950–2025, with stationarity tests and suitable transformations applied before developing the forecasting models, will be conducted. Forecasting accuracy, mean squared error (MSE), and root mean square error (RMSE), will be measured. Although ARIMA (3,1,3) provides a reliable means of capturing linear information, an Adaline-ANN model achieves a much higher level of predictive performance because it can capture complex temporal dynamics. This was shown by the substantial degree to which the neural network produced lower error values than the ARIMA model and by the greater stability with which they provided estimates for the period of time from 2026 to 2035. Overall, these findings support the effectiveness and adaptability of an Adaline-ANN approach to fertility forecasting and emphasize the significance of data-driven learning approaches for providing a more reliable basis for predictions and for assisting in the evidence-based planning of demographics.

KEY WORDS: Time series forecasting, ARIMA model, Adaline –ANN, Fertility rate, Demographic**.**

1. INTRODUCTION

Fertility rate, or the average number of offspring a mother produces during her reproductive years, is widely regarded as one of the most important demographic indicators of population growth, socio-economic circumstances, and levels of public health. Reliable fertility projections are critical for effective planning and resource allocation, especially in Iraq, where the recent political and economic changes have materially affected demographic trends and patterns. To better understand these trends, there must be a detailed quantitative analysis of historical data that not only accurately captures the temporal dynamics of the demographic process but also the structural dynamics (Preston, Heuveline & Guillot, 2001), which is further explained in Demography: Measuring and Modelling Population Processes.

The selection of an appropriate forecasting model presents some challenges. For example, while time series methods (and specifically, ARIMA) are commonly used to model both linear and non-stat94ionary data, the processes that produce population change (i.e., the demographic process), are also sometimes characterized by complex, non-

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linear patterns of behaviour. One alternative forecasting method that may provide sufficient flexibility to deal with the evolving nature of demographic data is artificial neural networks (ANN), for example, Adaline. However, the relative predictive performance of ANN and ARIMA models in highly volatile demographic environments (e.g., Iraq) is unknown (Box, Jenkins, Reinsel & Ljung, 2015), see Time Series Analysis: Forecasting and Control.

2. Methodology

The purpose of this study is to forecast the fertility rate in Iraq by using both ARIMA and Adaline-ANN models to compare the 4

relative suitability of these two frameworks for forecasting fertility trends based on historical time series data.

This research study will compare the ability of an ARIMA model and an Adaline - Artificial Neural Network (ANN) model to predict Iraq's fertility rates. In this research project, both models will be trained on historical time series data for Iraq's fertility rates. They will be tested and evaluated using several statistical metrics (Root Mean Square Error (RMSE), Mean Squared Error (MSE), etc.). The model with the most accurate predictions will be used to forecast Iraq's fertility rates from 1950 to 2025 and also to make predictions for the period 2026 - 2035.

The purpose of this research was to analyze and predict demographic trends by utilizing past fertility rate data for Iraq from 1950 to 2025 available in the Macrotrends database (also known as the 'data mining' website). Before analysis, the data must undergo pre-processing procedures such as stationary tests and normalization to ensure it is appropriate for time series analysis. In addition, ARIMA and Adaline-ANN were used for forecasting demographic trends. While the ARIMA model describes the linear temporal patterns through time, the Adaline-ANN model predicts linear relationships based on an adaptive learning scheme.

To evaluate the performance of each forecasting model, three performance criteria were utilized: RMSE (root mean square error) & MSE (mean square error). Each of these performance criteria provided an evaluation of how well the models fit data and how accurately they predicted future values. Following this analysis, the best performing model was selected to forecast future fertility rates of Iraq through 2035 and to provide comparisons of the ARIMA and Adaline-ANN models as prediction methods in time series analysis.

2.1 Forecasting Models

Demographic planning and resource allocation require knowledge of Iraq's future fertility rates. The ARIMA model (Box et al., 2015) is a statistical method for forecasting time series data that incorporates both linear and nonstationary patterns, while the Adaline neural network (Haykin, 2009) is an adaptive, dynamic method that provides a flexible, data-driven means of forecasting time series data. This research paper will discuss the underlying theory, assumptions, and purposes of both forecasting models with respect to time series data analysis.

2.2 Auto Regressive Integrated Moving Average ARIMA Model

The ARIMA (Autoregressive Integrated Moving Average) model has been established as a prime statistical method for making predictions about future values based on previously observed values of a variable because it is both flexible and has good theoretical foundations. It consists of three main components: an autoregressive (AR) structure, a moving average (MA) process, and a differencing operation which helps to account for non-stationarity within the data (Box, Jenkins, Reinsel, & Ljung, 2015). There are numerous examples of the application of this framework in many different fields; thus, ARIMA models are considered the standard approach to univariate time-series modelling.

2.2.1 Auto Regressive (AR) process:

The AR process models the current value of the series as a linear combination of its previous values and a stochastic error term. Mathematically, an AR process of order *p* is represented as:

$$\mathrm{X_t = c + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \emptyset_3 X_{t-3} + \cdots + \emptyset_p X_{t-p} + \varepsilon_t \quad t = 1,2,\ldots T} \qquad (1)$$

where X_t is the current value, c is a constant term, $\emptyset_i$ are the autoregressive coefficients, and $\varepsilon_t$is a white noise error term. This model captures the linear dependence between an observation and its lagged values

2.2.2 Moving Average (MA) process:

The MA process models the current value of the series as a linear combination of past error terms. An MA process of order *q* is expressed as

$$\mathrm{X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \theta_3 \varepsilon_{t-3} - \cdots - \theta_q \varepsilon_{t-q}} \qquad (2)$$

where θ_iAre the moving average coefficients representing the influence of previous shocks on the current observation.

2.2.3 Auto Regressive Moving Average (ARMA) process:

By combining AR and MA processes, the ARMA model captures both lagged observations and lagged errors:

$$\mathrm{X_t = c + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_3 \varepsilon_{t-3} - \cdots - \theta_q \varepsilon_{t-q}} \qquad (3)$$

ARMA models assume the time series is stationary. However, many real-world datasets, including fertility rates or airport passenger flows, exhibit trends or non-stationarity (Hamad et al., 2023)

2.2.4 Integrated component (I): ARIMA (p, d, q) model

The ARIMA model extends ARMA to non-stationary series by introducing differencing. For a series X_tThat is non-stationary, first-order differencing can be applied (Wei, 2006):

$$\mathrm{\Delta X_t = X_t - X_{t-1}} \qquad (4)$$

The general ARIMA (p, d, q) model is then expressed as

$$\mathrm{\Delta^d X_t = c + \emptyset_1 \Delta^d X_{t-1} + \cdots + \emptyset_p \Delta^d X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}} \qquad (5)$$

where *d* denotes the order of differencing

If $p = q = 0$ and $d = 1$, The model reduces to a **random walk**. ARIMA (p, d, q) which implies the next value is equal to the previous value plus a random error, reflecting a simple non-stationary process. The ARIMA model is highly flexible, allowing it to model a wide range of linear time series behaviours. AR captures the memory effect of past observations, MA captures the influence of past shocks or errors, and the integration component ensures stationarity (Box et al., 2015).

2.3 Adaline Neural Network (ANN) model

The Adaline neural network is a single-layer linear unit model that uses a bipolar activation function (+1, -1) for predicting continuous values (Widrow & Stearns, 1993). Unlike traditional perceptron's, Adaline minimizes the difference between predicted and actual outputs using the delta learning rule, which iteratively adjusts weights and bias to reduce the Mean Squared Error (MSE) across the dataset. The simplicity of the Adaline-ANN makes it particularly suitable for time series forecasting problems, such as predicting passenger traffic at airports (Widrow, & Lehr,1993).

The main difference between the perceptron and ADALINE is that the latter works by minimizing the mean squared error of the predictions of a linear function (Widrow & Lehr, 2002). This means that the learning procedure is based on the outcome of a linear function rather than on the outcome of a threshold function as in the perceptron. Mathematically, learning from the output of a linear function enables the minimization of a continuous cost or loss function. Continuous cost functions have the advantage of having well-defined derivatives, which facilitate training neural networks through gradient-based methods. This innovation opened the

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door to more complex algorithms such as non-linear multilayer perceptron, logistic regression, support vector machines, and others (Widrow & Stearns, 1993).

2.3.1 Structure of the Mathematical Model

The net input of the Adaline network is calculated as:

$$y_i^{in} = \sum_{i=1}^{n} w_i x_i + b \tag{6}$$

Where:

w_i is the weight associated with the $i-th$ input,

x_i is the $i-th$ input variable,

b is the bias term

n is the total number of input

The output is then compared to the target value t_i and the error is calculated using the squared difference (Widrow & Lehr, 1993):

$$\text{Error} = [t_i - y_i^{in}]^2 \tag{7}$$

The weights and biases are updated using the delta rule as follows:

$$w_i^{new} = w_i^{old} + \alpha(t_i - y_i^{in})x_i \tag{8}$$

$$b^{new} = b^{old} + \alpha(t_i - y_i^{in}) \tag{9}$$

Where $alpha\ is$ the learning rate that controls the adjustment step size. The process is repeated iteratively over all training samples until the stopping condition is met, which can be defined as minimal change in weights or when the error falls below a predefined threshold (Widrow & Lehr, 2002).

2.3.2 Algorithm Steps

1. Initialize weights w_i with small random values and set the learning rate α
2. For each epoch, repeat the following steps until the stopping condition is met:
   a. Present each input vector x_i to the network.
   b. Calculate the net input y_i^{in} and apply the activation function.
   c. Compute the error between predicted and actual output.
   d. Update the weights and bias according to the delta learning rule.

This iterative process ensures that the network gradually converges toward minimizing the MSE over the training data. (Haykin, 2009)

2.3.3 Interpretation

Adaline's structure & functionality allow it to be trained with linearly related points in a time series. It adjusts weight according to how much error there is, which smooths the rate of convergence. When applied to predicting the number of passengers flying from airport to airport, the Adaline Model can provide a good indicator of underlying trends as well as seasonal fluctuations, with other methods used to generate accurate predictions.

2.3.4 Structure of Adaline-ANN

The structure of the Adaline network is explained in Fig. 1, where each input x_i is multiplied by its corresponding weight w_i, summed together with a bias b, and passed through a linear activation function to produce the output. The error between the predicted and actual output is then used to update the weights iteratively (Widrow & Lehr, 2002; Widrow & Stearns, 1993).

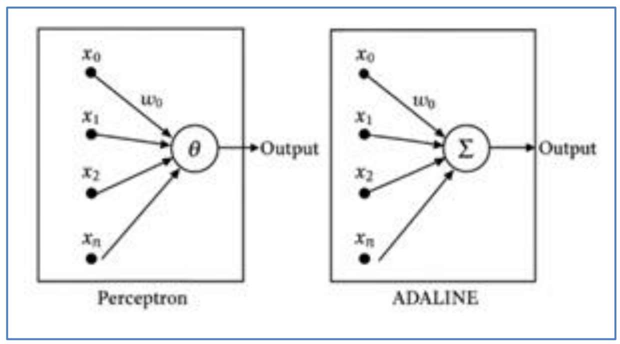

Fig.1: Structure of Adaline-ANN (Widrow et al.,1990)

2.4 Stationary Testing Using the Dickey–Fuller Test:

The Dickey-Fuller test assesses stationarity in time series data, identifying whether a unit root is present (Dickey & Fuller, 1979; Hamilton, 1994; Enders, 2014). Stationarity is essential for reliable forecasting with models like ARIMA. The test's formula is:

$$\Delta Y_t = \propto + \beta Y_{t-1} + \delta t + \epsilon_t \tag{10}$$

and

Where: $\Delta Y_t = Y_t - Y_{t-1}$ and

$\propto$: The intercept, or constant term, represents a fixed value that affects all observations in the time series. Including α\alphaα allows the test to account for a non-zero mean in the series.

β: The coefficient of Y_{t-1} , representing the effect of the previous time period's value on the current change.

δt represents a deterministic trend component ϵ_t is white noise

The following presumptions guide the test's execution:

H_0 :The unit root is present and is non-stationary.

H_1: The unit root does not exist and is stationary.

2.5 Measuring Forecast Accuracy

The Mean Squared Error (MSE) and Root Mean Square Error (RMSE) can be used to analyse the results of forecasting. MSE and RMSE are used to search for the accuracy of forecasting results with historical data (Hussein, et al, 2023). The smaller the value, the better the results of forecasting. MSE and RMSE is used to calculate the accuracy of forecasting methods, evaluate the accuracy of forecasts, compare the accuracy of forecasting techniques, and help o find an optimal method in the form of a percentage (Ahmed, et al, 2023). The way it works is that forecasting results are calculated by using equations (11) and (12), and later, the error value of each data is known. The smallest error value is the model with the best performance (Nguyen, et al, 2022). Here is the formula for MSE and RMSE

$$MSE = \frac{1}{n-1} \sum_{t=1}^{n} (y_i - \hat{y}_i)^2 \qquad (11)$$

$$RMSE = \sqrt{\frac{1}{n-1} \sum_{t=1}^{n} \left(y_i - \hat{y}_i\right)^2} \qquad (12)$$

Where:

x_i: Actual demand

$\hat{x}_i$: Forecast demand and

n: Time period count

3. Results Interpretation and Discussion

Annual time series data for the fertility rate in Iraq from 1950 to 2025, which was acquired using the Macrotrends database, was analysed to observe historical trends and make projections about future growth of the fertility rate in Iraq. Two models (ARIMA and Adaline artificial neural network) were utilized to analyse the fertility rate time series and generate estimates of future fertility rates. These data are graphically displayed in Figure 2. In trying to determine which forecasting model would provide the best estimate of fertility rates in Iraq between 2026 and 2035, the results from each model were compared and compared for consistency and predictability. All model estimates and parameter estimates were completed using the RStudio software package.

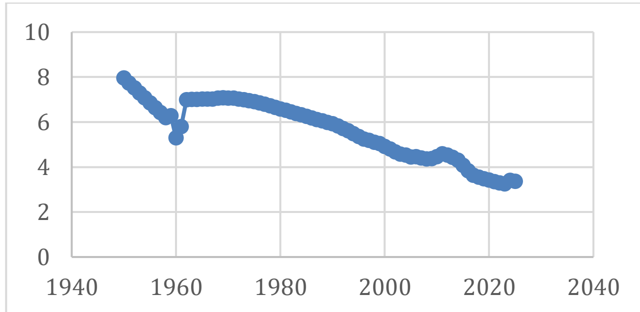

Fig. 2: Iraq Fertility Rate (1950-2025)

3.1 Stationary Testing Using the Dickey–Fuller Test:

The following presumptions guide the test's execution:

H_0 :The unit root is present and is non-stationary.

H_1: The unit root does not exist and is stationary.

Table (1) Augmented Dickey–Fuller (ADF) Test for Original Series

Test Statistic	p-value	Decision (α = 0.05)	Conclusion
-2.0899	0.5388	Fail to reject H_0	The series is non-stationary

The Augmented Dickey–Fuller (ADF) test applied to the original time series yielded a Dickey–Fuller statistic of −2.0899 with a p-value of 0.5388. As the p-value exceeds the 0.05 significance level, the null hypothesis of a unit root cannot be rejected, indicating that the series is non-stationary. Accordingly, differencing is required to achieve stationarity.

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Table (2) Augmented Dickey–Fuller (ADF) Test after First Differencing

Test Statistic	p-value	Decision (α = 0.05)	Conclusion
-3.5903	0.04016	Reject H_0	The series is stationary

Following the application of first-order differencing, the Augmented Dickey–Fuller (ADF) test yielded a test statistic of −3.5903 with a p-value of 0.04016. Because the p-value is below the 0.05 significance threshold, the null hypothesis of a unit root is rejected, indicating that the differenced series is stationary. Consequently, a differencing order of d=1 is appropriate for ARIMA or related time series modelling.

3.2 Forecasting Based on the Estimated ARIMA Model

As in the previous process, the data on fertility rate will be processed by using ARIMA models. First, predetermine that the data used has already been qualified. The table (3) displays the mean square error (RMSE) and root mean square error (RMSE) for various ARIMA models tested for forecasting fertility rate. The objective is to determine which ARIMA model provides the highest forecasting accuracy.

Table (3): Performance Measures Used to Compare Different ARIMA Models

Models	MSE	RMSE	Models	MSE	RMSE
ARIMA(1,1,1)	0.03852	0.196265	ARIMA(2,2,3)	0.035937	0.189572
ARIMA(1,1,2)	0.038524	0.196276	ARIMA(2,3,1)	0.046802	0.216338
ARIMA(1,1,3)	0.037988	0.194905	ARIMA(2,3,2)	0.042788	0.206852
ARIMA(1,2,1)	0.041461	0.203619	ARIMA(2,3,3)	0.036229	0.190339
ARIMA(1,2,2)	0.036072	0.189925	ARIMA(3,1,1)	0.038431	0.196037
ARIMA(1,2,3)	0.035934	0.189563	ARIMA(3,1,2)	0.03793	0.194756
ARIMA(1,3,1)	0.06457	0.254107	ARIMA(3,1,3)	0.035613	0.188713
ARIMA(1,3,2)	0.042185	0.20539	ARIMA(3,2,1)	0.037902	0.194685
ARIMA(1,3,3)	0.036473	0.190979	ARIMA(3,2,2)	0.035953	0.189614
ARIMA(2,1,1)	0.038526	0.19628	ARIMA(3,2,3)	0.035966	0.189648
ARIMA(2,1,2)	0.036836	0.191926	ARIMA(3,3,1)	0.046198	0.214938
ARIMA(2,1,3)	0.037794	0.194406	ARIMA(3,3,2)	0.038605	0.196481
ARIMA(2,2,1)	0.039772	0.19943	ARIMA(3,3,3)	0.036417	0.190834
ARIMA(2,2,2)	0.035931	0.189556			

Based on the experimental results, the ARIMA (3,1,3) model was selected as the most accurate model. This model achieved the lowest MSE of 0.035613 and the lowest RMSE of 0.188713%, indicating that it provides the best fit for the data among all the models tested.

3.3 Estimated Model forecasting of Adaline-ANN model

The fertility rate data were processed using Adaline-ANN models to evaluate their forecasting performance. Before modelling, the data were verified to ensure quality and suitability for analysis. The parameters of the Adaline-ANN model were estimated using an optimization method as follows:

The Model:

$$\Delta_{y_t} = -0.0727 + 0.2597\Delta_{y_{t-1}} + -0.4608\Delta_{y_{t-2}} + 0.2413\Delta_{y_{t-3}} + -0.3199\Delta_{y_{t-4}} + 0.121\Delta_{y_{t-5}} + -0.2437\Delta_{y_{t-6}} + 0.045\Delta_{y_{t-7}} + -0.2148\Delta_{y_{t-8}} + -0.0264\Delta_{y_{t-9}} + -0.1695\Delta_{y_{t-10}}.$$

is a 10th-order Autoregressive (AR (10)) model applied to first differences of the series y_t .

The object is to catch both the short-term relation and the dynamic behaviour of the change of the variable in question. Error measures (MSE and RMSE) for the Adaline-ANN model operating between lag orders of 1 and 10 are shown in Table 4).

Table (4): Comparison of Model Selection Results for Adline-ANN models (lag1-10)

Lag	MSE	RMSE
1	0.042232	0.205504
2	0.040816	0.20203
3	0.039045	0.197599
4	0.038826	0.197043
5	0.038688	0.196692
6	0.038473	0.196146
7	0.03857	0.196392
8	0.038024	0.194997
9	0.038441	0.196064
10	0.019999	0.141418

The data from Table 4 shows a decrease in forecasting errors due to the increase in lag value, which indicates that more past observations will be able to model the underlying patterns associated with trends for fertility rates. The main finding is that lag-10 produced the least MSE (0.019999) as well as the least RMSE (0.141418) compared to all other lag values, which means that there was a substantial reduction in prediction error when using lag-10 as opposed to lower lags. Therefore, this indicates that Adaline ANN with larger lag orders generate more accurate fertility rate forecasts.

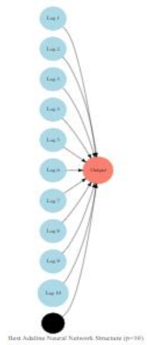

Fig. 3: Best Adaline -ANN structure (lag=10)

There is a single-layer Adaline artificial neural network comprising 10 inputs concurrently connected to 1 output using a direct linear weighting scheme. This network is used to predict future values of a time series based on previously observed values of the time series.

3.4 Comparative Analysis of ARMA and Adaline –ANN models

The comparative study of ARIMA and Adaline artificial neural network models compares the ability both models possess to model and predict time series. This is accomplished by comparing the differences between the way in which the structure and learning mechanisms have been created between the ARIMA and Adaline artificial neural network and whether either one of those models produces a more accurate and reliable forecast based upon either type of data that exhibits a linear trend or one that may contain some other element of evolution to the data pattern

Table (5): Choose the best model based on the accuracy of the models

Criteria	ARIMA (3,1,3)	Adaline-ANN
MSE	0.035613	0.019999
RMSE	0.188713	0.141418

Table 5 summarizes the forecasting accuracy metrics for both models, the ARIMA (3,1,3) and the Adaline-ANN, by means of comparing their respective MSE and RMSE. The MSE value for ARIMA (3,1,3) is 0.035613, and its RMSE value is 0.188713, while the MSE value for the Adaline ANN model is 0.019999 and the RMSE value for the Adaline ANN is 0.141418. These results suggest that Adaline ANN has better forecasting accuracy than ARIMA (3,1,3) based on having lower MSE and RMSE values than those of ARIMA (3,1,3).

3.5 Estimated Model forecasting of ARIMA (3,1,3) and Adaline –ANN models

Forecasting will reveal that Adaline-ANN has a more accurate predictive capability than other time series methods like the ARIMA (3,1,3) method, as shown by comparing forecasted values to respective mean squared error (MSE) and root mean square error (RMSE) values. The results of this study show that the Adaline-ANN will consistently produce smaller amounts of predictive errors than the ARIMA (3,1,3), which suggests that the Adaline-ANN model can be considered more accurate and reliable than using ARIMA (3,1,3) when attempting to predict the fertility rate of Iraq. It is therefore recommended that both the ARIMA (3,1,3) and Adaline-ANN models be used in making future estimates of the fertility rate in Iraq, since both methods provide a good representation of the underlying pattern; forecasted values for 2026 through 2035 are included in table 5 and indicate that the forecasted line from the Adaline-ANN will have a significantly smoother and more accurate form of prediction than that from the ARIMA (3,1,3).

Table (6) Forecasted values obtained from ARIMA (3,13) and Adaline-ANN models

Years	**Forecast Value**	
	ARIMA (3,1,3)	ANN
2026	3.291648	3.343187562
2027	3.335021	3.347085301
2028	3.311011	3.318813588
2029	3.324302	3.328211888
2030	3.316945	3.322953827
2031	3.321018	3.314112211
2032	3.318763	3.306290961
2033	3.320011	3.297890965
2034	3.31932	3.280376872
2035	3.319703	3.244310699

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According to the results presented in Table 6, the forecasted values for 2026 to 2035 for both the ARIMA (3,1,3) and Adaline-ANN models show that the Adaline-ANN has slightly higher projections than the ARIMA most years. Moreover, the Adaline-ANN has a smoother curve than ARIMA, which suggests that it captures the data's underlying pattern better than ARIMA. Therefore, it can be concluded that the Adaline-ANN will be the better forecasting model, due to the Adaline-ANN having greater accuracy and consistency in its predictions compared to ARIMA.

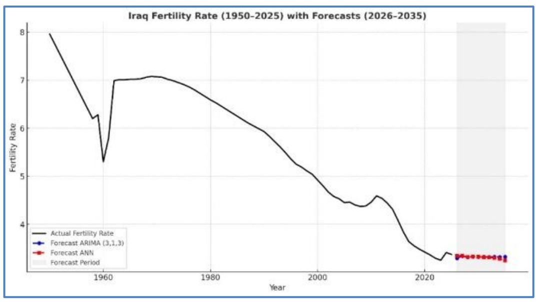

Fig.4: Plot Forecast value of the ARIMA (3,13) and Adaline-ANN models

4. Research Findings and Discussion

The results of comparing the performance of ARIMA and Adaline-ANN models when forecasting Iraq's fertility rates found large discrepancies between their abilities to predict this series. The ARIMA Model (3,1,3) showed an average fit, producing an MSE of 0.035613 and an RMSE of 0.188713, meaning it was fit for estimating linear types of behaviour in the time series pattern of this data series. The Adaline-ANN Model, on the other hand, demonstrated better performance overall, particularly when evaluating higher lag orders; specifically, the lag10 ANN produced an MSE of 0.019999 and an RMSE of 0.141418 compared to ARIMA (3,1,3). Therefore, it can be concluded that in addition to having more accurate forecasts than the ARIMA model, the Adaline-ANN Model was able to identify and predict complex temporal relationships that extend beyond the normal linear behaviour that would be expected from the ARIMA forecasts, resulting in smoother and more accurate forecasts than ARIMA. Furthermore, the Adaline-ANN Model had a significantly greater ability than ARIMA to represent both short-term fluctuations in fertility rates and long-term fertility trends.

5. Conclusions and Recommendations

The conclusions obtained from this study provided key findings and suggested a variety of actionable recommendations to support ongoing and future studies as well as to inform future practices.

5.1 Conclusions

The conclusions were derived from analytical findings, as follows;

1. An analysis of fertility rates in Iraq through 2025 would be conducted using both Adaline-ANN and ARIMA (3,1,3) models.
2. Statistically, ARIMA provides a good fit to the time series data; the linear components (trends) of the data were well represented with ARIMA.
3. Adaline-ANN had the lowest errors (MSE of ARIMA; RMSE of ARIMA) when compared with ARIMA and Adaline-ANN; Adaline-ANN consistently produced lower mean squared errors (0.019999) and root mean squared errors (0.141418) than ARIMA.
4. Artificial Neural Networks are superior to ARIMA models in terms of their ability to model complex temporal dependencies and phenomena associated with fertility trends through the use of multiple lag structures.
5. Adaline-ANN provides a much better representation of the short-term and long-term fluctuations resulting from unexpected fertility variations.

5.2 Recommendations

1. Because it provides a higher level of accuracy and reliability than the others, the Adaline-ANN is the model to use as the preferred model for forecasting the fertility rate in Iraq from 2026 to 2035.
2. The ARIMA model should continue to serve as the standard baseline reference for linear forecasting,

but it can be used in conjunction with ANN to create a hybrid-modelling framework.

3. Additional research should include examining the benefits of using a hybrid ARIMA-Adaline-ANN model that combines the advantages of both models.

4. Incorporating additional socioeconomic and demographic variables into the model would increase forecast precision and provide more insight into policy decisions.

References

1. Ahmed, D. H., Mohamad, S. H., & Karim, R. H. R. (2023). Using Single Exponential Smoothing Model and Grey Model to Forecast Corn Production in Iraq during the period (2022-2030). University of Kirkuk Journal For Administrative and Economic Science, 13(3).
2. Box, G. (2013). Box and Jenkins: time series analysis, forecasting and control. In A Very British Affair: Six Britons and the Development of Time Series Analysis During the 20th Century (pp. 161-215). London: Palgrave Macmillan UK.
3. Box, G. E. P., & Jenkins, G. M. (1970). Time Series Analysis: Forecasting and Control. Holden-Day. a publishing company based in San Francisco, California
4. Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time Series Analysis: Forecasting and Control (5th ed.). Hoboken, NJ: John Wiley & Sons.
5. Faqe, A. P. D. M. M., Hamad, A. P. D. A. S., & Mohamad, A. L. S. H. (2023). Forecasting Life-Expectancy in Iraq During the Period (2022-2035) Using Fuzzy Markov Chain. Journal of Business Economics for Applied Research, 5(3).
6. Hamad, A. P. D. A. S., Faqe, A. P. D. M. M., & Mohamad, A. L. S. H. (2023). Forecasting Life-Expectancy in Iraq During the Period (2022-2035) Using Fuzzy Markov Chain. University of Fallujah, Journal of Business Economics for Applied Research, 5(3), 347-372.
7. Hamilton, J. D. (1994). Time series analysis. Princeton University Press.
8. Hussein, M. M. F., Saeed, A. A., & Mohamad, S. H. (2023). Comparison Markov Chain and Neural network models for forecasting population growth data in Iraq. University of Kirkuk Journal For Administrative and Economic Science, 13(4).
9. Hussein, O. M. M. (2024). A Comparison of ARIMA and GVM (1, 1) models for Forecasting Rice Production in Iraq. Journal of Kurdistani for Strategic Studies, (11).
10. Haykin, S. (2009). Neural Networks and Learning Machines (3rd ed.). Upper Saddle River, NJ: Pearson Education.
11. Moreno, J. J. M. (2011). Artificial neural networks applied to forecasting time series. Psicothema, 23(2), 322-329.
12. Preston, S. H., Heuveline, P., & Guillot, M. (2001). Demography: Measuring and Modeling Population Processes. Malden, MA: Blackwell Publishers.
13. Wang, L., Zou, H., Su, J., Li, L., & Chaudhry, S. (2013). An ARIMA-ANN hybrid model for time series forecasting. Systems Research and Behavioral Science, 30(3), 244-259.
14. Wei, W. W. S. (2006). Time Series Analysis: Univariate and Multivariate Methods. Pearson Addison Wesley.
15. Widrow, B., & Lehr, M. A. (1993). Adaptive neural networks and their applications. International Journal of Intelligent Systems, 8(4), 453–507.
16. Widrow, B., & Lehr, M. A. (1990). 30 years of adaptive neural networks: perceptron, Madaline, and backpropagation. Proceedings of the IEEE, 78(9), 1415-1442.

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ملخص

يُعدّ التنبؤ بمعدلات الخصوبة ذا أهمية بالغة في كيفية إدارة الموارد، ووضع السياسات، وتخطيط الفئات السكانية، لا سيما في البلدان التي تشهد تغيرات اجتماعية واقتصادية كالعراق. هدفت هذه الدراسة إلى تطوير التنبؤات الديموغرافية من خلال تحليل دقة التنبؤ لنموذجين من نماذج السلاسل الزمنية، وهما نموذج المتوسط المتحرك المتكامل التلقائي (ARIMA) وشبكة عصبية اصطناعية خطية تكيفية (Adaline). سيتم تحليل بيانات معدل الخصوبة السنوي للفترة من 1950 إلى 2025، مع إجراء اختبارات الاستقرار وتطبيق التحويلات المناسبة قبل تطوير نماذج التنبؤ. سيتم قياس دقة التنبؤ، ومتوسط مربع الخطأ (MSE)، وجذر متوسط مربع الخطأ (RMSE). على الرغم من أن نموذج ARIMA (3,1,3) يوفر وسيلة موثوقة لالتقاط المعلومات الخطية، إلا أن نموذج Adaline-ANN يحقق مستوى أعلى بكثير من الأداء التنبؤي لقدرته على استيعاب الديناميكيات الزمنية المعقدة. وقد تجلى ذلك في انخفاض قيم الخطأ التي أنتجتها الشبكة العصبية بشكل ملحوظ مقارنةً بنموذج ARIMA، وفي استقرار تقديراتها للفترة الزمنية من 2026 إلى 2035. وبشكل عام، تدعم هذه النتائج فعالية وقابلية تطبيق منهجية Adaline-ANN في التنبؤ بالخصوبة، وتؤكد على أهمية مناهج التعلم القائمة على البيانات في توفير أساس أكثر موثوقية للتنبؤات، وفي المساعدة على التخطيط الديموغرافي القائم على الأدلة.

الكلمات المفتاحية: التنبؤ بالسلاسل الزمنية، نموذج ARIMA، Adaline-ANN، معدل الخصوبة، الديموغرافيا.

پوختە

پێشبینیکردنی ڕێژەی منداڵبوون کاریگەرییەکی گەورەی هەیە لەسەر چۆنیەتی بەڕێوەبردنی سەرچاوەکان، پەرەپێدانی سیاسەت و پلاندانان بۆ گروپە دیمۆگرافییەکان، بەتایبەتی لەو وڵاتانەی کە گۆڕانکاری کۆمەڵایەتی و ئابووری وەک عێراق ئەزموون دەکەن. ئامانجی ئەم توێژینەوەیە پێشخستنی پێشبینی دیمۆگرافی بوو بە شیکردنەوەی وردی پێشبینیکردنی دوو مۆدێلی زنجیرە کاتییەکان، ئەوانیش مۆدێلی تێکڕای جووڵاوی یەکگرتووی خۆپاشکەوتنەوە (ARIMA) و تۆڕێکی دەماری دەستکردی دەمارە هێڵییەکانی گونجاو (Adaline). شیکارییەک بۆ داتای ساڵانەی ڕێژەی منداڵبوون لە ساڵانی 1950-2025، لەگەڵ تاقیکردنەوەکانی جێگیربوون و گۆڕانکارییە گونجاوەکان کە پێش پەرەپێدانی مۆدێلەکانی پێشبینیکردن بەکارهێنراون، ئەنجام دەدرێت. وردی پێشبینیکردن، مامناوەندی هەڵەی چوارگۆشە (MSE)، و مامناوەندی هەڵەی چوارگۆشەی ڕەگ (RMSE)، دەپێورێت. هەرچەندە ARIMA (3،1،3) ئامرازێکی جێی متمانە بۆ گرتنی زانیاری هێڵی دابین دەکات، بەڵام مۆدێلی Adaline-ANN ئاستێکی زۆر بەرزتر لە ئەدای پێشبینیکردن بەدەست دەهێنێت چونکە دەتوانێت داینامیکی کاتی ئاڵۆز بگرێت. ئەمە بەو ڕادەیە دەرکەوت کە تۆڕی دەماری بەهای هەڵەی کەمتری بەرهەمهێناوە لە چاو مۆدێلی ARIMA و بە سەقامگیری زیاتر کە خەمڵاندنەکانیان بۆ ماوەی کات لە ساڵی 2026 تا 2035 پێشکەش کردووە. بە گشتی، ئەم دۆزینەوانە پشتگیری لە کاریگەری و گونجاندنی ڕێبازی Adaline-ANN دەکەن بۆ پێشبینیکردنی منداڵبوون و جەخت لەسەر گرنگی ڕێبازەکانی فێربوونی داتا-بزوێنەر دەکەنەوە بۆ دابینکردنی بنەمایەکی متمانەپێکراوتر بۆ پێشبینیکردن و بۆ یارمەتیدان لە پلاندانانی دیمۆگرافی لەسەر بنەمای بەڵگە.

وشە سەرەکییەکان: پێشبینی زنجیرە کاتییەکان، مۆدێلی ARIMA، Adaline –ANN، ڕێژەی منداڵبوون، دیمۆگرافی.