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Using ANNs and ARIMA Models to Make Accurate Forecasts for Palestinian Official Statistics Based on Simulation and Empirical Applications

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Abstract

Accuracy of forecasts of economic indicators is a major concern of statistical and economics departments. Over the past three decades there has been growing literature on applications of artificial neural networks (ANNs) to business and financial domains. ANNs do not assume restrictions during the modeling process because ANNs recognize the relationships between the variables. Thus, ANNs have the capability of executing the forecasting for different types of models without a pre- knowledge about the relationship between explanatory and response variable. In this paper, we demonstrate how ANNs can be used to make forecasts of artificial and real data sets. Furthermore, we will compare the accuracy of the ANN forecasts to those obtained by more classical time series models as autoregressive integrated moving average (ARIMA), using exhaustive simulation and real data on size of the population in the Palestinian Territories.

Keywords:
Population,
Artificial Neural Networks,
ARIMA,
Forecasting,
Time Series.

1. Introduction:

The Time series analysis is used for numerous applications such as: size of population forecasting, yield projections, consumer price index prediction, census analysis, and many more. An autoregressive (AR) process is a model that future observations are predicted completely based on the past values of the time series, a moving average (MA) process is a model that future observations are predicted completely based on the past values of random disturbances, and an autoregressive-moving average (ARMA) process is a model that combines both past values of the time series and past random disturbances (Box et al., 2015).

The most important objectives of time series analysis are: first, determining the characteristic of the time series by the sequence of values; secondly, forecasting future values of the time series variable. Both of these goals assume that the pattern of observed time series data is determined and formally described.

Building on work on forecasting of the time series literature, we are examining the price one must pay for using ANNs under suboptimal conditions. We are testing different values of first order autoregressive parameterization, AR(1), under which relative efficiency of the ANNs model to ARIMA model, determining ranges of AR(1) coefficient, ϕ, for which ARIMA is efficient and quantifying the effect of trend on the efficiency of the ARIMA estimator. Furthermore, we have conducted an exhaustive simulation study setup to examine the relative efficiency of ANNs to that of ARIMA models. In particular, how do ARIMA models perform in forecasting in case of linear modeling?

Data Source: We use the data set of size of the population in the Palestinian Territories from Palestinian Central Bureau of Statistics (PCBS), http://www.pcbs.gov.ps. We considered annually data sets for size of the population over the period of the 1997-2016.

This paper is organized as follows. Section 2 illustrates an overview of the literature, Section 3 represents an overview of ANN terminology and describes a methodology for neural model identification. We present the comprehensive simulation study in section 4. This simulation is designed to compare the performance of different values of AR(1) and sample sizes and determination of the effect of the efficiency of ARIMA models compared to ANNs models. Empirical results for fitting models for size of the population in the Palestinian Territories by using ANNs and ARIMA models are shown in section 5. Finally, concluding remarks and suggestions for future work on the comparison of ANNs and ARIMA for different models are given in section 6.

2. Literature Review:

There are extensive researches have been conducted that compared ANNs with other classical time series models, see for example White and Safi (2016), Buado (2016), Safi (2013), Valipour et al. (2012), Aksoy and Dahamsheh (2009), Düzgün (2008), Zhang and Kline (2007), Lee and Chen (2005), Abhyankar, et al. (1997), among many others.

More recently, White and Safi (2017) compared the forecast accuracy for the two methods (ARIMA and ANNs) using data from the Palestine stock market. They showed that the ANN models produced the most accurate forecasts at each level of granularity. In addition, the forecast for ANN and ARIMA models based on larger and finer data sets were more accurate than those on the smaller data sets. The ANNs will become more accurate as the more information is fed into the model (i. e. larger data sets). ANN may often be more preferable than assuming an ARIMA model when the actual model is non-linear.

Buado (2016) studied the monthly electricity sales in Algeria over the period 1/1/2006 - 31/12/2012. Buado found that among many other models, ARMA(6,6) has the smallest Akaike's information criterion (AIC) and revealed that ARIMA model was superior to ANN model.

Baker & Iqelan (2015) evaluated the performance of ARIMA, and ANNs for forecasting the number of births per month in Gaza Strip, over the time period January 2000 to December 2013. Four forecasting accuracy measures are used, namely: MSE, MAE, RMSE, and MAPE. The model has the lowest value of these measures is superior to the other models. The major findings are that MLP model outperforms SARIMA, Jordan Recurrent Neural Network model (JRNN) outperforms SARIMA and MLP model, Elman Recurrent neural network (ERNN) model outperforms JRNN model, and Radial Bais feed forward neural model (RBFNN) outperforms JRNN.

Grant (2014) examined the ANN model versus simple moving average (SMA), linear regression, and multivariate adaptive regression splines (MARSplines). The ANN model outperformed the other forecasting methods tested with a mean absolute percentage error (MAPE) of 3.9% as compared to the SMA, linear regression, and MARSplines MAPEs of 7.7%, 17.3%, and 7.0% respectively. Furthermore, the ANN model obtained an absolute maximum error (AME) of 18.2% as compared to the SMA, linear regression, and MARSplines AMEs of 26.2%, 45.1%, and 22.5%, respectively.

Rodrigues et al. (2014) have used ANN for Short Term Load Forecasting (STLF) for household electric energy consumption for 93 real households, in Lisbon, Portugal, between February 2000 and July 2001. The ANNs are distinguished to be an appropriate methodology for modeling hourly and daily energy consumption and load forecasting. They concluded that a feed-forward ANN and the Levenberg-Marquardt algorithm provided a good performance and the ANN approach provides a reliable model for forecasting household electric energy consumption.

Shrivastava et al. (2012) mentioned that there are two main faults of the numerical and statistical models: Firstly, the statistical models are not suitable to study the highly nonlinear relationships between response variable and the explanatory variables. Secondly, there is no explicit way to find the best independent variables. Artificial Neural Network came into existence in 1986 which is able to get rid of these two faults and it can take into account the complex of non-linearity problems much better than the existing traditional statistical techniques.

Valipour et al. (2012) used monthly discharges data from 1960 to 2007 in Dez reservoir inflow at the Taleh Zang station. They showed dynamic autoregressive ANN used is superior to static autoregressive ANN, because of the output delay effect as input to network and increase in the power of network training compared to autoregressive static neural network and in general compared to the ARMA and ARIMA models in both training and forecasting stages. The root mean square error and mean bias error are used for these comparisons.

Dhamija and Bhalla (2011) used data of exchange rates, they showed that ANNs model can be efficiently used in predicting for this data and consequently recommended in purpose of trading strategies. They showed that ANNs can jointly and effectively extract the non-linear functional form as well as model parameters.

Chen and Lai (2011) introduced ARIMA model and ANN to forecast the hourly wind speed one to four hours ahead. They showed that ANN model outperformed ARIMA model in forecasting short-term hourly wind speed. If the variance is extremely high, they mentioned that combined models or numerical weather predicting method is needed to improve the results.

Düzgün (2008) compared ANN and ARIMA models' success in Turkish GDP forecast. The study is accomplished on the Turkish economy, and the data period from the first quarter of 1987 to the third quarter of 2007. MAE, MSE RMSE, and Theil's U criteria were used for comparison purpose. The results showed that ARIMA model was superior to ANN model in GDP forecasting.

Kandil et al. (2006) mentioned a simple multi-layered feedforward ANN. The major finding is that the potential for better results exists and can be accomplished by using: (1) more advanced types of ANN, (2) better selection of input variables, (3) better ANN architecture and (4) better selection of the training set.

Somvanshi et al. (2006) have showed that ANN model can be used as an appropriate forecasting tool to forecast the rainfall, which outperforms the ARIMA model. Mohammadi, et al. (2005) forecasted Karaj reservoir inflow using data of snow melting. The results showed that ANN has lower significant faults as compared with ARMA methods, and regression analysis.

Mohammadi et al. (2005) used different methods for predicting spring inflow to the Amir Kabir reservoir in the Karaj river watershed. They used three different methods, ANNs, ARIMA, and regression models. The main finding of their results is ANN outperformed the other models.

Yao and Tan (2000) discussed that traditional time series analysis does not perform well on economic time series. Economic data are not simple ARIMA models, white noise, random walks, or simple linear models. The high volatility and complexity lead to the suggestion of using ANN models for forecasting purposes.

Darbellay & Slama (2000) examined the dependence structure of the electric load time series of the Czech Republic. The main finding is that the forecasting performance of a linear model and nonlinear models were not very different. These models were, respectively, an ARIMA model and a ANN.

Toth et al. (2000) used the ANN and ARMA models to forecast rainfall. They have found that ANN provides significant improvement in the flood forecasting accuracy in comparison to the use of simple rainfall prediction approaches.

Since the 1990’s, ANN models have been used to model financial data. Kohzadi, et al. (1996) compared ANNs and ARIMA models to forecast US monthly live cattle and wheat cash prices from 1950 to 1990. They showed that the ANNs forecasts were more efficient than ARIMA models, which were used as a benchmark. They conjectured that the neural network model superior on ARIMA because the data is non-linear or disorganized behavior, which could not be completely captured by the linear ARIMA model.

3. Overview of Artificial Neural Networks (ANNs):

3.1 Introduction:

Recently, many articles concluded that ANNs outperform any other time series traditional models in case of nonlinearities between the response variable and explanatory variables. The reason behind this highly performance of ANNs over the other models is ANNs recognize the relationships essential in the variables. Thus, ANNs have the capability of executing the forecasting for different types of models without a pre-knowledge about the relationship between explanatory and response variable.

Definition 3.1. An Artificial Neural Network (ANN) is an information-processing paradigm that is inspired by the way biological nervous systems such as brain, process information, (Dongare et al., 2012).

The ANNs is a function of a set of derived inputs, called hidden nodes. The hidden nodes are nonlinear functions of the original inputs. In common, there are up to two layers of hidden nodes. Increasing the number of nodes in the first layer, or adding a second layer, makes the neural network more flexible. The three essential features of an ANN are the basic processing elements referred to nodes; the network architecture describing the connections between nodes; and the training algorithm used to find values of the network parameters for performing a particular task (Allende et al., 2002).

The main advantage of a neural network model is that it can efficiently model different response surfaces. Given enough hidden nodes and layers, any surface can be approximated to any accuracy. The main disadvantage of a neural network model is that the results are not easily interpretable, since there are intermediate layers rather than a direct path from the X variables to the Y variables, as in the case of regular regression (SAS Institute Inc. 2013).

Neural networks are very flexible models and have a tendency to overfit data. When thathappens, the model predicts the fitted data very well, but predicts future observations poorly.

Definition 3.2. The functions applied at the nodes of the hidden layers are called activation functions. The activation function is a transformation of a linear combination of the X variables.

There are four types of activation functions, namely, the linear activation function, the logistics function, the hyperbolic tangent function, and the Gaussian function.

1. The Linear activation function is most often used in combination with one of the non-linear activation functions. In this case, the linear activation function is placed in the second layer, and the non-linear activation functions are placed in the first layer. For a continuous Y variable, if only linear activation functions are used, the model for the Y variable reduces to a linear combination of the X variables.
2. The logistics function is used for a qualitative or ordinal Y variable, in this case the model reduces to a logistic regression. The logistic function is:

$$f(x) = \frac{1}{1+e^{-x}} \qquad (3.1)$$

3. The hyperbolic tangent function is a sigmoid function. This function transforms values to be between -1 and 1, and is the centered and scaled version of the logistic function. The hyperbolic tangent function is:

$$f(x) = \tanh(x) = \frac{1-e^{-2x}}{1+e^{-2x}} \qquad (3.2)$$

4. The Gaussian function is used for radial basis function behavior, or when the response surface is Gaussian (normal) in shape. The Gaussian function is:

$$f(x) = e^{-x^2} \qquad (3.3)$$

where *x* is a linear combination of the X variables.

3.2 FeedForward Neural Network:

In literature, there are many types of ANNs, the most commonly types are:

- FeedForward neural networks,
- Radial basis function (RBF) neural networks,
- Back-propagation (BP) neural networks
- Kohonen self-organizing neural networks,
- Learning vector quantization,
- Recurrent neural network,
- Modular neural networks.

The feedforward neural network was the first and from my point of view the simplest type of ANNs. In this network the data moves in one way-forward: From the input nodes data goes through the hidden nodes and to the output nodes. There are no cycles in the network. Feedforward networks can be constructed from different types of units, e.g. binary McCulloch-Pitts nodes, the simplest example being the perceptron. Continuous nodes, frequently with sigmoidal activation, are used in the context of backpropagation of error.

There are two types of perceptron network, single and multi-layer perceptron. The simplest kind of neural network is a single-layer perceptron network, which consists of a single layer of output nodes; the inputs are fed directly to the outputs via a series of weights. In this way, it can be considered the simplest kind of feed-forward network (Auer, 2008). The other type of perceptron is a multilayer perceptron (MLP) is a feedforward ANN model that maps sets of input data onto a set of appropriate outputs. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. (Rosenblatt, 1961; Rumelhart et al., 1985). MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable (Cybenko, 1989)

From the library *forecast* in *R*-Software, the *nnetar* function is used to perform the analysis of ANNs. The *nnetar* function is used to fit neural networks. This function is described as feed-forward neural networks with a single hidden layer and lagged inputs for forecasting univariate time series. The *nnetar* function fits an Neural Network Autoregressive models. By default, 25 networks with random starting values are trained and their predictions averaged.

4. The Simulation Study:

4.1 The Simulation Setup:

The Root Mean Squared Error (RMSE) is one of the most commonly as measure of forecasts accuracy because of its theoretical relevance in statistical modeling, Hyndman & Koehler (2006). RMSE is used when comparing forecast methods on a single data set. This means, RMSE is preferable to use if all forecasts are measured on the same scale.

Suppose $x_1, x_2, \ldots, x_n$ denotes the data set, and we split it into two parts: the training data $x_1, x_2, \ldots, x_t$ and the test data $x_{t+1}, x_{t+2}, \ldots, x_n$. To check the accuracy of the forecasting method, we will estimate the model's parameters using the training data, and forecast the next $n-t$ observations. Then, we compare the test data with these forecasts, (White and Safi, 2017).

Definition 4.1. The Root Mean Squared Error (RMSE) is defined as:

$$RMSE = \sqrt{\sum_{i=t+1}^{n} \frac{\left(x_i - \hat{x}_{i|t}\right)^2}{n-t}} \tag{4.1}$$

Definition 4.2. The efficiency of the forecast ARIMA model relative to that of ANNs model in terms of the RMSE, Ω, is given by:

$$\Omega = \frac{RMSE_1}{RMSE_2}, \tag{4.2}$$

where $RMSE_1$ and $RMSE_2$ are the RMSE from the ARIMA and ANN, respectively. A ratio less than one indicates that the forecast performance of the ARIMA model is more efficient than ANNs model, and if Ω is close to one, then ARIMA forecast model is nearly as efficient as the ANNs model. Otherwise, the ARIMA model performs poorly (White & Safi, 2016).

To evaluate the relative efficiency of RMSE in a linear regression with autocorrelated disturbances depends mainly on the design structure of the models (ANNs and ARIMA) and the autoregressive parametrizations. We constructed a comprehensive simulation study to compare the performance of ANNs corresponding to ARIMA. The models were produced of the form:

$$\begin{aligned} Z_t &= g(t) + \zeta_t \\ \zeta_t &= \phi\zeta_{t-1} + u_t,\ t = 1, 2, \ldots, N \end{aligned} \tag{4.3}$$

The disturbances follow an autoregressive model of first order, AR(1), with coefficient $0 < \phi < 1$ and u_t are N(0,1). Sixty six cases are considered in the simulation: six finite series lengths (N = 10, 20, 30, 50, 100, and 500) and eleven autoregressive coefficients selected in steps 0.1 $(\phi = 0.1, 0.2, \ldots, 0.9)$ and two very extreme values 0.05 and 0.95 are used. For each case, We further generated 1000 observations for each of N and ϕ. The autoregressive coefficients values were chosen to provide the worst and best performances of ANNs and ARIMA models. The model coefficients b_0, and b_1 were each chosen to be equal one. R functions were used to conduct the simulation.

In this simulation, we used AR(1) because most of the economic data series were annual. This explains the frequent usage of this model, as forecasting of more complexity time series models may be difficult without using more advanced and specialized statistical software (Safi & White, 2006).

4.2 The Simulation Results:

In this section, we discuss the relative efficiencies of RMSE of ARIMA to ANNs for the sixty six time series simulated data. The complete numerical results are presented in Table 1 for the different chosen of sample sizes and selected values of $0 < \phi < 0.9$.

For very small sample size (N=10), we see that regardless of different values of $0 < \phi < 0.9$, the relative efficiency for RMSE of the ARIMA as compared to the ANNs model is greater than one. For example, when $\phi = 0.5$, the relative efficiency for RMSE of the ARIMA to ANNs equals 1.1958. This result indicates that RMSE for ARIMA equals 19.58% more than that of ANNs model. This result emphasizes that ANNs is more efficient than ARIMA for every situation considered here. This suggests that the forecasting results using ANNs may often be better than ARIMA for very small sample size.

However, there are examples where ANNs performs poorly as well. For example, when the sample size is small (N=20) with $\phi \le 0.3$. Consider N =20 and $\phi = 0.1$, the relative efficiency for RMSE of the ARIMA to ANNs is 0.8698. This result indicates that RMSE for ARIMA model equals 86.68% of ANNs model.

While for the moderate values of ϕ, $0.4 \le \phi \le 0.6$, and small sample size, ARIMA is more efficient than ANNs. For example, when N =20 and $\phi = 0.5$, the relative efficiency for RMSE of the ARIMA to ANNs is 0.9682. This result indicates that RMSE for ARIMA model equals 96.82% of ANNs model.

Additionally, for large values of ϕ, $0.7 \le \phi \le 0.95$, and small sample size, ANNs is more efficient than ANNs. For example, when N =20 and $\phi = 0.95$, the relative efficiency for RMSE of the ARIMA to ANNs is 1.0437. This result indicates that RMSE for ARIMA equals 4.37% more than that of ANNs model. Additionally, the results based on T=30 mimic the same as T=20.

The poor performance of ARIMA relative to ANNs is most marked when the sample size is very small (N = 10) and the value of the autoregressive coefficient is large for N=20 and 30.

Table 1 Relative Efficiencies for different Sample Sizes and Selected ϕ's

Parameter (ϕ)	Sample Size (N)					
	10	20	30	50	100	500
0.05	1.1365	0.8504	0.8014	0.7814	0.7530	0.6123
0.10	1.1634	0.8698	0.8254	0.8010	0.7692	0.5926
0.20	1.1605	0.9042	0.8597	0.8360	0.8071	0.6032
0.30	1.1707	0.9197	0.8916	0.8646	0.8345	0.6243
0.40	1.2039	0.9929	0.9211	0.8950	0.8607	0.6314
0.50	1.1958	0.9682	0.9432	0.9235	0.8882	0.6425
0.60	1.2125	0.9890	0.9630	0.9471	0.9005	0.6380
0.70	1.2498	1.0064	0.9797	0.9640	0.9269	0.6439
0.80	1.2521	1.0192	0.9929	0.9768	0.9430	0.6869
0.90	1.2623	1.0418	1.0104	0.9896	0.9515	0.6799
0.95	1.2521	1.0437	1.0131	0.9940	0.9576	0.6373

Furthermore, for moderate sample sizes (N=50 and 100), and for all selected ϕ, ARIMA is more efficient than ANNs. For example, when N =50 and $\phi = 0.4$, the relative efficiency for RMSE of the ARIMA to ANNs is 0.8950. This result indicates that RMSE for ARIMA model is 89.50% of ANNs model. The performance of ANNs becomes nearly as efficient as ARIMA for large ϕ. For example, when N =50 and $\phi = 0.95$, the relative efficiency for RMSE of the ARIMA to ANNs is 0.9940. This result indicates that RMSE for ARIMA model is 99.40% of ANNs model.

Finally, regardless of the autoregressive coefficients, ARIMA performs much better than ANNs for large sample size (N=500). For example, when $\phi = 0.9$ and N=500, the relative efficiency for RMSE of the ARIMA to ANNs is 0.6799. This result indicates that RMSE for ARIMA model is 67.99% of ANNs model.

To summarize the most finding for the simulation study, we have discussed the relative efficiency of the ARIMA to ANNs for different sample sizes and selected autoregressive coefficients. In investigating the simulation results in this section, we observe the following significant results. First and foremost we notice that regardless of the selected autoregressive coefficients for very small sample size (N=10), the efficiency for ANNs model is higher than ARIMA model.

This result shows that the ANNs models produced the most accurate forecasts when the disturbances follow AR(1) at each value of autoregressive coefficients for small sample sizes.

Secondly, ANNs performs as great as ARIMA in most cases for the selected small and moderate sample sizes for large values of autoregressive coefficients, $(\phi \ge 0.7)$. However, for the other choices of ϕ's , ANNs performs poorly and produce inaccurate forecasts in this case. Finally, regardless of the ϕ's in case of large sample size, ANNs performs much less efficient than ARIMA.

5. The Empirical Results:

This section introduces the empirical results on In-Sample Training for fitting models for size of the population in the Palestinian Territories by using the two different approaches, ANNs and ARIMA models. We use data sets for size of the population in the Palestinian Territories over the period of the 1997-2016. The forecasting results are shown in the next sub-sections.

In this section we present the basic definitions of the autocorrelation function (ACF) and partial autocorrelation function (PACF). Data description, methodology of the analysis, fitting and forecasting models, respectively, are shown in separate sub-sections.

Definition 5.1. For a covariance stationary time series $\{Y_t\}$, the autocorrelation function ρ_k is given by:

$$\rho_k = Corr(Y_t, Y_{t-k}) \text{ for } k = 1, 2, 3, \ldots \quad (5.1)$$

ACF is a good guide of the order of the MA(q) model since it cuts off after lag q (i.e. ρ_k k = 0 for k > q). On the other hand the ACF tails off for AR(p) model.

Definition 5.2. If $\{Y_t\}$ is normally distributed time series, then the PACF at lag k is given by:

$$\phi_{kk} = Corr(Y_t, Y_{t-k} | Y_{t-1}, Y_{t-2}, \ldots, Y_{t-k+1}) \quad (5.2)$$

PACF is a good indicator of the order of the AR(p) model since it cuts off after lag p (i.e. ϕ_{kk} = 0 for k > p). On the other hand the PACF tails off for MA(q) model, (Cryer and Chan, 2008).

5.1 Data Description:

The time-series plots of size of the population in the Palestinian Territories, West Bank, and Gaza Strip, are presented in Figure 1. From these plots, we can see that the data is very much linear over time and show no fluctuations. This indicates that one must be using ARIMA models as they may provide accurate forecasts instead of using more complicated models as ANNs.

The sample ACF and PACF are produced. We show only here PACFs in Figure 2 for Palestinian Territories, West Bank, and Gaza Strip, respectively. The plots give quite clearer indication about the order of AR of the time series data for size of the population. Based on this plot, one must choose an AR(1) model for these time series.

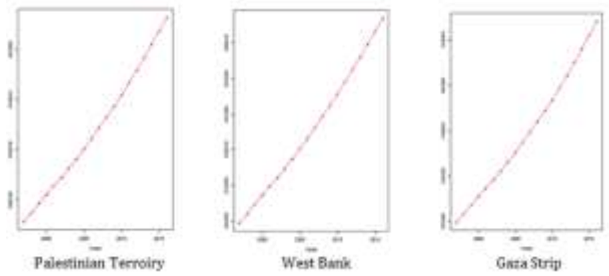

Figure 1 *Data for Size of the Population in the Period 1997-2016*

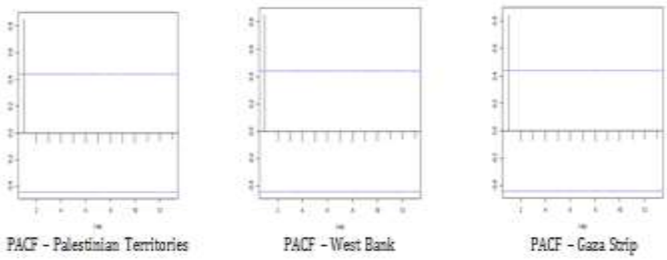

Figure 2 *PACFs for the Population*

5.2 Methodology of the Analysis:

For each of the data sets, models fit on the training sample were used to forecast the test sample. Two types of forecast models were used: ARIMA and ANNs models. In this statistical analysis for the underlying data sets, 20% of the sample size is used as the testing sample. A training sample is used for the model building, and the testing sample is used for the model validation.

R statistical software was used for fitting ANNs and ARIMA models for size of the population in the Palestinian territories. The *nnetar* function from the R package *forecast* was used to fit neural networks. By default, 20 networks with random starting values are trained and their predictions averaged (Hyndman, 2012).

On the other hand, The *auto.arima* command in R was used to fit the ARIMA model. This algorithm uses maximum likelihood estimation (MLE) to fit an ARIMA(*p, d, q*) model for different choices of *p*, *d* and *q*, and then compares Akaike Information Criteria to determine the best model (White & Safi, 2016).

5.3 Fitting Models:

Table 2 shows the RMSE as a measure of forecasting accuracy for the two methods, and the relative efficiencies of the error of ARIMA model to the

ANNs model for size of the population in the Palestinian Territories.

Since the ANNs model depends on a random starting values, the final model used was an average of 20 networks, each of which was a 1-1-1 network with 4 weights. Table 5.1 shows that for ANNs method, the RMSEs values for size of the population in the Palestinian Territories, West Bank, and Gaza Strip equal 6470.047, 3352.255, and 3178.707, respectively.

In addition, the best ARIMA model for each data set is ARIMA(1,2,0). Table 5.1 shows also that for ARIMA method, the RMSEs values for size of the population in the Palestinian Territories, West Bank, and Gaza Strip equal 3355.843, 1686.417, and 1899.412, respectively.

Table 2 *Accuracy Measures and Relative Efficiencies*

Palestinian Territories	West Bank	Gaza Strip	Model
3355.843	1686.417	1899.412	ARIMA
6470.047	3352.255	3178.707	ANNs
0.5187	0.5031	0.5975	ARIMA/ANNs

Comparing the measures of forecast accuracy in Table 2 between the models, we see that for size of the population in the Palestinian Territories, the relative efficiency of ARIMA to ANNs equals 0.5187. This result indicates that the RMSE for the ARIMA model equals 51.8% of ANNs model. We obtained similar results for the population in West Bank and Gaza Strip. The relative efficiencies of ARIMA to ANNs for size of the population in West Bank and Gaza Strip equal to 0.5031 and 0.5975, respectively. Accordingly, ARIMA is much more efficient than ANNs for the population in Palestine. These results reveal that ARIMA perform better than ANNs for small data set (N=20). Consequently, ARIMA forecasts are the most accurate in this case. These results mimic the same as the simulation results mentioned earlier.

In addition, the empirical results with three real data sets on size of the Palestinian territories and the simulation results indicate that the ARIMA model can be an effective and significant way to ameliorate and make efficient forecasting accuracy achieved by ANNs. Therefore, it can be used as an appropriate alternative model for forecasting purposes, especially when higher forecasting accuracy is required.

5.4 Forecasting Models:

Table 3 shows the actual and predicting results for size of the population in the Palestinian Territories, West Bank, and Gaza Strip based on ANNs and ARIMA (1,2,0) models.

Table 3 *Actual and Prediction of ANNs and ARIMA for the Population in 2013-2017*

Year	Actual data	Prediction	
		ANNs	ARIMA
Palestinian Territories			
2013	4,420,549	4,390,530	4,419,906
2014	4,550,368	4,471,815	4,547,645
2015	4,682,467	4,536,302	4,675,999
2016	4,816,503	4,585,157	4,804,681
West Bank			
2013	2,719,112	2,702,552	2,718,962
2014	2,790,331	2,746,817	2,789,507
2015	2,862,485	2,781,556	2,860,387
2016	2,935,368	2,807,612	2,931,452
Gaza Strip			
2013	1,701,437	1,688,100	1,700,795
2014	1,760,037	1,725,296	1,757,697
2015	1,819,982	1,755,254	1,814,776
2016	1,881,135	1,778,270	1,871,934

It is quite clear that the forecast error of ARIMA is much less than that of ANNs. This result indicates that ARIMA model fits size of the population data much better than ANNs model. Therefore, we conclude that ARIMA model for forecasting is much more accurate and efficient than the ANNs model.

Table 4 shows the forecasting results for size of the population in the Palestinian Territories, West Bank, and Gaza Strip in the period 2017-2020 based on ANNs and ARIMA (1,2,0) models.

Table 4 *Forecasting Values of ANNs and ARIMA for the Population in 2017-2020*

Year	Forecasting	
	ANNs	ARIMA
Palestinian Territories		
2017	4,620,797	4,933,539
2018	4,646,047	5,062,491
2019	4,663,555	5,191,494
2020	4,675,509	5,320,523
West Bank		
2017	2,826,454	3,002,620
2018	2,839,703	3,073,845
2019	2,848,832	3,145,101
2020	2,855,030	3,216,375
Gaza Strip		
2017	1,795,268	1,929,128
2018	1,807,440	1,986,337
2019	1,815,956	2,043,552
2020	1,821,815	2,100,771

6. Concluding Remarks and Future Researches:

In this paper, we compared the forecast accuracy for two methods using data from size of the population in the Palestinian territories. In addition to comparing the methods, six finite series lengths were used: (N = 10, 20, 30, 50, 100, and 500) and eleven autoregressive coefficients selected in steps 0.1 $(\phi = 0.1, 0.2, \ldots, 0.9)$ and two very extreme values 0.05 and 0.95 are used. The data exhibits considerable invariability and linearity.

The simulation results indicate that the ARIMA models produced the most accurate forecasts for almost all cases except for very small sample size, when N=10. Furthermore, the forecast for ARIMA models based on larger data sets was more accurate than ANN on the smaller data sets.

In addition, the empirical results for size of the population in Palestinian territories show that the ARIMA models outperform ANN and consequently produced more accurate forecasts than ANN for all of the three data sets for size of the population in Palestinian Territories, West Bank, and Gaza Strip.

The results of this study agreed with the two studies mentioned in the literature section, Buado's who studied the monthly electricity sales in Algeria and Düzgün's study in Turkish GDP forecast.

As a rule of thumb, we conclude that ARIMA models may often be more preferable than assuming ANN model when the actual model is linear. In other words, it is sometimes better to ignore the complexity of ANNs model and use an ARIMA model rather than to incorrectly assume the model is ANNs.

The significance of this research can be summarized in two important issues. First, the results add to the growing body of literature that recommends the use of ARIMA for forecasting data. Secondly, it's the first research – up to my knowledge – about forecasting one of most important official statistics as size of the population in the Palestinian territories.

The next step recommended for the future research is to compare the performance of more traditional methods of nonlinear time series models with ANNs in the context of economic data. Finally, the long range goal is the creation rules of thumb which will assist the researchers when deciding which forecasting model to use.

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استخدام نماذج الشبكات العصبية الصناعية و(أريما) للحصول على تنبؤات دقيقة للإحصاءات الرسمية الفلسطينية بناء على المحاكاة والتطبيقات التجريبية

تعتبر دقة التنبؤ للمؤشرات الاقتصادية مصدر اهتمام كبير لدى الدوائر الإحصائية والاقتصادية. يوجد تزايد في الأدبيات حول تطبيقات الشبكات العصبية الاصطناعية في المجالات المالية والتجارية وذلك خلال العقود الثلاثة الماضية. لا تفترض الشبكات العصبية الصناعية قيود أثناء عملية النمذجة، لأنها تتعرف على العلاقة بين المتغيرات. لذلك، فإن الشبكات العصبية الصناعية لديها القدرة على إجراء التنبؤ لأنواع مختلفة من النماذج دون معرفة مسبقة عن العلاقة بين المتغير المُفَسِّر (المستقل) والمُستجيب (التابع). في هذا البحث، نقوم بوصف كيفية استخدام الشبكات العصبية الصناعية في التنبؤ لبيانات حقيقية وافتراضية. بالإضافة إلى مقارنة دقة تنبؤ نماذج الشبكات العصبية الصناعية والسلاسل الزمنية التقليدية مثل نماذج الانحدار الذاتي والمتوسطات المتحركة التكاملية، وذلك باستخدام محاكاة شاملة وبيانات حقيقية عن عدد السكان في الأراضي الفلسطينية.

كلمات مفتاحية:
عدد السكان،
الشبكات العصبية الصناعية،
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التنبؤ،
السلاسل الزمنية.