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Using Neural Network Auto-Regression to Forecast the Palestinian Unemployment Rate

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Abstract: Historical data show that the unemployment rate in Palestine remains high, leading to significant challenges. Predicting unemployment rates would assist decision-makers in economic and financial planning, enabling them to implement preventive measures to mitigate their economic and social consequences. Research indicates that classical time series models may fail by producing a white noise error, given that unemployment rates are non-stationary and nonlinear in nature. This study empirically investigates the behavior of the Palestinian quarterly unemployment rate by addressing the research question: How efficient are neural network auto-regression (NNAR) models in forecasting the short-term Palestinian unemployment rate? Using quarterly unemployment rate data from 2001 to 2023, the study applies the NNAR model to determine the short-run state of the Palestinian unemployment rate. The model's performance is evaluated using accuracy measures, including mean absolute error (MAE), mean absolute percentage error (MAPE), mean absolute scaled error (MASE), and root mean square error (RMSE). For comparison purposes, the study applies seasonal auto-regressive moving average (SARIMA), Holt-Winter's (HW) additive, and HW's multiplicative models. Findings indicate that NNAR[1,1,10]4 is the optimal model, outperforming conventional models. The results also reveal that the Palestinian unemployment rate is expected to remain high, fluctuating between

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23.8% and 28.1%. This study contributes to the existing literature by further exploring the effectiveness of the NNAR approach in capturing nonstationary and nonlinear behaviors, in order to explain variations in the Palestinian unemployment rate, as compared to traditional linear models. The economic implications of this high and sustained unemployment rate suggest weak demand in the Palestinian economy, indicating a reduced need for workers, which may lead to decreased working hours or layoffs. Policymakers in Palestine will find these results helpful.

keywords: unemployment rate; NNAR; forecasting; accuracy; Palestine.

1 Introduction

Unemployment remains a significant global challenge, hindering economic and financial development and giving rise to adverse social effects. Its consequences extend beyond individual job loss, impacting not only the economy but also individual well-being, social stability, and overall life satisfaction (Abugamea, 2018; Pohlan, 2019). The International Labor Organization (ILO) commonly measures unemployment using the unemployment rate, which represents the proportion of unemployed individuals in the total labor force (ILOSTAT, 2023). This serves as a reliable indicator of a country's labor market conditions, reflecting the equilibrium between labor supply and demand and providing insights into the overall performance of the economy. This indicator has garnered significant attention in assessing progress toward the achievement of Sustainable Development Goal 8, which aims to promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all (UN, 2017).

Effective forecasting of the unemployment rate is crucial for informing economic decision-making and facilitating the development of impactful policies. It enables early detection of socioeconomic issues and strategic planning for their mitigation. The reliability of such forecasts is thus crucial to ensure their accuracy and usefulness (Davidescu et al., 2021b). Numerous time series models have been widely employed for global unemployment forecasting, and prior studies suggest asymmetries and nonlinearities in the unemployment rate data across various countries. A key implication in time-series analysis stemming from this behavior is its inconsistency with a linear process of generating data featuring symmetrically distributed time series (Chakraborty et al., 2021).

Several previous studies have utilized various forecasting methods to predict the short-term behavior of unemployment across different countries, although in many cases they remain inconclusive in terms of forecasting accuracy. The classical linear time series methods have been demonstrated to be effective forecasting results for some European countries (Davidescu et al., 2021b; Dritsaki, 2016; Dumičič et al., 2015; Etuk et al., 2012; Jelena et al., 2017; Dritsakis et al., 2018; Rublikova and Lubyova, 2013; Sun, 2023; Vicente et al., 2015), and for out-of-sample forecasts for the Canadian unemployment rate (Khan Jaffur et al., 2017). Meanwhile, Nagao et al. (2019) found that classical nonlinear models outperformed linear time series models in forecasting the unemployment rate in the USA. Advancements in contemporary statistics and machine learning have provided scholars with non-linear prediction tools, including artificial neural networks (ANN), deep learning, decision trees (DT), random forests (RF), and support vector machines (SVM), among other techniques (Atsalakis et al., 2007; Gogas et al., 2022; Katris, 2020; Sermpinis et al., 2014). ANN models have demonstrated promising accuracy in predicting unemployment across the asymmetric business cycle in Canada, Japan, Romania, Turkey, the UK and the USA (Davidescu et al., 2021b; Moshiri and Brown, 2004; Peláez, 2006; Yamacli and Yamacli, 2023; Wang and Zheng, 2009). For example, Davidescu et al. (2021b) have shown that univariate neural network autoregression (NNAR) outperforms traditional time series models. Prior research has also developed hybrid approaches which combine linear and nonlinear components of time series. Such approaches have shown an ability to produce more accurate forecasting results and improve complex autocorrelation structures, particularly for multivariate time series models (Ahmad et al., 2023; Chakraborty et al., 2021; Shi et al., 2022; Yurtsever, 2023). Nevertheless, asymmetries persist in unemployment rate forecasting, and elimination of these asymmetries is expected to pose a significant challenge (Galbraith and van Norden, 2019; Katris, 2020).

The current study focuses on forecasting the Palestinian unemployment rate for different reasons. First, previous research and data from recent years for Palestine reveal that the Palestinian labor market has faced a persistent and elevated unemployment rate and significant volatility; a close association with political circumstances; and is unevenly distributed among gender, age groups, and geographic area (Daoud, 2006; Hillis et al., 2018; PCBS, 2022). According to the Palestinian Central Bureau of Statistics (PCBS, 2022), the unemployment rate reached 26.4% in 2021, and was more pronounced among females (42.9% for females versus 22.4% for males), the youth (aged 15–24 years, 37.2% for males and 64.5% for females), and in the Gaza Strip (46.9%) compared to the West Bank (15.5%). Second, the current research identifies gaps in the literature concerning the forecasting of the Palestinian unemployment rate, specifically in the context of NNAR models. While conventional univariate time series and ANN models are widely applied globally, there is a shortage of studies focusing on Palestine and employing nonlinear forecasting methods. Most economic indicators, such as unemployment, exhibit non-stationary and nonlinear behaviors. Consequently, classical time series models such as ARIMA models may fail to capture nonlinear variations. Specifically, ARIMA models are designed for forecasting univariate stochastic time series. Nevertheless, NNAR models have demonstrated their ability to yield more accurate results, while being less complex and more easily interpretable compared to other classical methods (Davidescu et al., 2021b; Hyndman and Athanasopoulos, 2018). Third, the results of several previous studies yield mixed and controversial findings regarding the most effective and accurate forecasting models for the unemployment rate. Some studies have highlighted that there is no universally accepted and globally recognized model, and the selection of the best model depends on factors such as the available data, forecasting period, and country-specific characteristics (Będowska-Sŏjka, 2015; Galbraith and van Norden, 2019; Katris, 2019, 2020). The precision of future predictions directly influences the effectiveness of policies and decisions. The significance lies not only in the subject of forecasting but also in the crucial aspect of forecast accuracy. Therefore, the study establishes the following research question to be addressed through empirical investigation: How efficient are NNAR models in forecasting the short-term Palestinian unemployment rate?

The current research aims to forecast the quarterly Palestinian unemployment rate in the short-run utilizing unemployment rate data over the period 2001Q1 to 2023Q2. The study applies a univariate nonlinear NNAR model to account for variations in the unemployment rate, considering both nonstationary and nonlinearity within the time series data. The data have been divided into training and testing datasets. The model has first been trained using the training dataset, then validated for its accuracy using the testing dataset. The findings of this research show that NNAR(1,1,10)[4] performs well for both in-sample and out-of-the-sample forecasts. Then, the model is used to predict the unemployment rate in the short run, and the results show that the Palestinian unemployment rate is anticipated to persist at elevated levels, fluctuating between 23.8% and 28.1% in the near future (2023Q3 – 2025Q4). These projections indicate that the Palestinian labor market has exceeded its equilibrium and is characterized by lower labor demand and higher labor supply. This result also indicates poor performance of the Palestinian economy. For robustness and comparison purposes, the study uses SARIMA, HW's additive, and HW's multiplicative models. The results highlight the NNAR model as the most effective for modeling the short-run behavior of the Palestinian unemployment rate. This study contributes to the literature in various ways. First, we have demonstrated that the estimated NNAR model provides promising results in controlling for nonstationary and nonlinear behavior to explain variations in the Palestinian unemployment rate. Second, we have further explored the effectiveness of NNAR models as compared to traditional linear time series models for forecasting unemployment rates. Finally, to the best of the authors' knowledge, this study is among the few conducted in the Palestinian labor market, and offers valuable insights into designing policies and strategies intended to reduce the unemployment rate in Palestine.

2 Literature Review

Unemployment is an economic challenge characterized by a mismatch between labor demand and supply which originates from dysfunctions within the labor market. It emerges as a consequence of decreased demand in the economy, in which a reduced demand for labor leads to diminished working hours or layoffs. Unemployment has been shown to have detrimental effects on individuals' life satisfaction, living standards, and mental health (Abugamea, 2018; Pohlan, 2019). It also influences food security (Haini et al., 2023), and has been recognized as a contributing factor to the risk of social exclusion (Popîrlan et al., 2021) as well as being detrimental to an individual's social class position and cultural environment (Ali et al., 2013). An effective approach to address these issues must include implementing proactive measures and policies for unemployment, highlighting the critical importance of forecasting.

Accurate forecasting of the unemployment rate plays a critical role in economic and financial planning. The literature shows that various statistical and econometric forecasting methods have been developed to predict the unemployment rate across different countries and have been tested to improve forecasting accuracy. These forecasting approaches range from classical time series models to more complex machine learning and innovative methods. However, empirical research has reached mixed conclusions regarding the best models for forecasting accuracy (Katris, 2020, 2019).

The most common traditional linear time series approach is the Box-Jenkins methodology, which includes autoregressive integrated moving average (ARIMA), seasonal ARIMA (SARIMA), autoregressive conditional heteroscedasticity (ARCH), and linear generalized autoregressive conditional heteroscedasticity (GARCH) models (Box et al., 2015). This approach has been widely applied to unemployment data across various countries and has demonstrated effectiveness in short-term forecasting (Dritsaki, 2016; Dritsakis and Klazoglou, 2018; Jelena et al., 2017; Mahipan et al., 2013; Mamingi et al., 2014; Sun, 2023). A study by Rublikova and Lubyova (2013) indicated that a combination of SARIMA(0,1,2)(0,1,1)[12] and GARCH(1,1) demonstrated superior performance in forecasting the unemployment rate in Slovakia. Furthermore, a study by Mahipan et al. (2013) predicted the unemployment rate in Thailand, demonstrating that the Box-Jenkins approach is more efficient and accurate in forecasting the monthly unemployment rate in Thailand compared to an artificial neural network (ANN), with consistent results and a tendency to decrease. Specifically, the SARIMA(0,1,1)12 model has demonstrated greater efficiency with lower forecasting accuracy measures, such as MAPE and RMSE. Mamingi et al. (2014) demonstrated that the SARIMA model outperformed the basic structural time series (BSTS) and general structural time series (GSTS) in forecasting the quarterly unemployment rate in Barbados. They also highlighted its suitability for policy decision-making. In Greece, Dritsaki (2016) predicted the monthly unemployment rate using the Box-Jenkins approach utilizing monthly data covering the period from April 1998 to September 2015. The study indicated that the SARIMA(0,2,1)(1,2,1)[12] model performed well, closely aligning forecasted values with actual unemployment rates. A study by Jelena et al. (2017) predicted unemployment rates for 28 European countries using SARIMA models, concluding that SARIMA(2,1,1)(12,2,12)[12] was the most effective model for monthly unemployment rates from 2000 to 2015. Moreover, Dritsakis et al. (2018) applied the Box-Jenkins methodology to forecast the Greek unemployment rate from 1980 to 2013, showing that the most suitable model for the unemployment rate during this period is ARIMA (1,2,1). However, this finding was not consistent with Dritsaki (2016). In the USA, Dritsakis and Klazoglou (2018) applied the Box-Jenkins methodology to forecast the monthly unemployment rate utilizing data over the period 1955 - 2017, revealing that the most suitable model for this period is SARIMA(1,1,2)(1,1,1)12-GARCH(1,1). Meanwhile,Kyung and Nam (2019) found that the ARIMA model is effective and precise in short-term predictions of US unemployment rates, but that its accuracy diminishes for long-term forecasting without access to comprehensive information. A recent study conducted by Sun (2023) demonstrated the effectiveness of ARIMA models in predicting the global unemployment rate.

Nonlinear classical time series models have been also used to forecast unemployment rates. These methods have been proposed to capture asymmetries existing in the unemployment rate series. For example, Floros (2005) showed that the MA(4)-ARCH(1) model yielded superior forecasts for the UK unemployment rate for the entire forecasting period from January 1996 to December 2002, in comparison to moving average (MA) and autoregressive (AR) models. Lahiani and Scaillet (2009) showed that autoregressive fractionally integrated moving average (ARFIMA) outperformed threshold autoregressive (TAR) and systematic ARFIMA models for modeling the unemployment rate in the USA. Furthermore, Kurita (2010) demonstrated the effectiveness of ARFIMA model for the Japanese unemployment rate data. Additionally, a study by Khan Jaffur et al. (2017) forecasted the seasonally adjusted monthly unemployment rate in Canada using both linear and nonlinear models. They highlighted that asymmetries in the Canadian unemployment rate were better captured using nonlinear models, and identified various models for out-of-sample forecast periods, with an ARMA(3,3) model performing well for 3 to 9 months ahead, and an ARMA(3,4) model excelling for the 12-month horizon. Over a 24-month forecast period, an MA(1)–GARCH(1,1) model proved more effective, while an MA(5) model was better for forecasting the unemployment rate 36 to 84 months ahead. In the USA, Nagao et al. (2019) found that the classical nonlinear TAR model outperformed linear models in predicting short-term seasonally adjusted monthly unemployment data. Davidescu et al. (2021a) employed both univariate and multivariate approaches to forecast the unemployment rate in Romania. The empirical results indicated that the self-exciting threshold autoregressive (SETAR) and vector error correction model (VECM) produced similar results with respect to accuracy, reflecting the preceding period of the COVID-19 pandemic accurately. A study conducted by Simionescu and Cifuentes-Faura (2022) predicted national and regional Spanish youth unemployment using Google trend indices. The study employed VECM and Bayesian vector autoregressive (VAR) models for national data, while for regional data it applied Bayesian panel data models and fixed effects models. The findings revealed that nonlinear models utilizing Google trends yielded more accurate results. However, Golan and Perloff (2004) found that the nonparametric approach using a higher-dimensional simplex technique outperforms linear and nonlinear time series models in forecasting US unemployment rates, even with extensive data. They attribute this to nonlinear behavior in the data-generating process. The study also validated this method's efficacy in modeling monthly and quarterly unemployment data.

Smoothing methods have also been used to forecast unemployment rates. A study by Dumičič et al. (2015) employed smoothing methods to select the most accurate forecasting method for predicting the unemployment rate in some selected European countries. They demonstrated that in the context of Greece, HW's additive model emerged as the most effective for forecasting the unemployment rate. For Spain and Portugal, the double exponential smoothing model exhibited superior performance, while HW's multiplicative model proved more accurate for forecasting unemployment rates in Croatia and Italy. Moreover, Gostkowski and Rokicki (2021) compared different forecasting methods for predicting the unemployment rate in Poland, showing that HW's multiplicative and quadratic regression models demonstrated superior forecasting performance and accuracy when contrasted with HW's additive, naïve, and ARIMA models.

In the ongoing progress of modern statistics, researchers have demonstrated growing interest in employing machine learning methods, including ANNs, deep learning, DT, RF, and SVM, among other techniques, to forecast the unemployment rate (Atsalakis et al., 2007; Gogas et al., 2022; Husin et al., 2023; Katris, 2020, 2019; Sermpinis et al., 2014; Wang and Zheng, 2009; Yamacli and Yamacli, 2023). The results of various previous studies showed that ANN models have proven to be more accurate in predicting the unemployment rates for both the short run and the long run. Furthermore, these models showed to be effective in accounting for non-linearity of the unemployment rate data and successfully captured the asymmetries of the business cycle and economic uncertainty for different countries (Moshiri and Brown, 2004; Peláez, 2006; Olmedo, 2014; Yamacli and Yamacli, 2023; Wang and Zheng, 2009). A study conducted by Stasinakis et al. (2016) explored the efficacy of Radial Based Function Neural Networks (RBFNN) for forecasting unemployment in the USA. They also assessed the significance of the Kalman filter and support vector regression as techniques for combining forecasts. They highlighted that RBFNN exhibited better performance as compared to the individual performance of all models. Katris (2020) conducted a study to forecast the monthly seasonally adjusted unemployment rates for 22 Mediterranean, Nordic, Baltic, Benelux, and Balkan countries using various time series and machine learning methods. The results highlighted that there is no universally accepted model, and that both the forecasting horizon and geographic location should be considered in selecting an approach. The empirical findings revealed that FARIMA models were the preferable approach for 1-step ahead forecasts, while for 12-step forecasts, neural network approaches achieved results comparable to FARIMA-based models. Nonetheless, the HW model was found to be more suitable for 3-step forecasts. Another study by Gogas et al. (2022) forecast the unemployment rate in the Eurozone, utilizing monthly unemployment rates from April 1998 to September 2019. The study applied three different machine-learning approaches, namely DT, RF, and SVM. They revealed that RF exhibited one of the highest levels of forecasting accuracy when compared to DT and SVM methodologies. Furthermore, Husin et al. (2023) predicted the unemployment rate in Malaysia by employing distinct ANN models for males and females. The findings indicated that the projected unemployment rate for both genders will remain consistently stable until 2030. Yamacli and Yamacli (2023) conducted a study forecasting the unemployment rate in Turkey from August 1, 2008, to August 31, 2022, using both ARIMA and ANN. They compared the forecasting accuracy of both methods and found that ARMA (2,1) emerged as the optimal model for predicting the unemployment rate in Turkey, exhibiting the lowest forecasting accuracy measures, including R^2, RMSE, MAE, and MAPE. However, during the COVID-19 period, ANNs demonstrated a lower prediction error as compared to ARMA (2,1), suggesting that ANNs are more accurate in forecasting the unemployment rate under conditions of economic uncertainty.

Nonetheless, a limitation of ANN methods is their inability to identify the optimal network architecture. To overcome this limitation, recent literature has suggested the NNAR model, which resembles a 'white box,' fitting a feed-forward neural net with one hidden layer to any time series dataset, incorporating lagged values of the series as inputs (Teräsvirta et al., 2005). A comparative analysis was conducted by Davidescu et al. (2021b) to compare forecasting accuracy in modeling the Romanian monthly unemployment rate from January 2000 to December 2020. The study evaluated the predictive accuracy and performance of various forecasting methods, including exponential smoothing, ETS (error, trend, seasonal), NNAR, and SARIMA models, for both in-sample and out-of-sample predictions. The results showed that HW's multiplicative model outperformed others for in-sample forecasts. However, for out-of-sample forecasts, SARIMA demonstrated superior performance based on MAPE values, while the NNAR model performed well across MAE and RMSE values. Nevertheless, the Diebold-Mariano test identified NNAR as the best model for a single forecast horizon in the testing dataset.

Finally, previous research has proposed hybrid approaches that combine both linear and nonlinear models (Ahmad et al., 2023; Chakraborty et al., 2021; Shi et al., 2022; Yurtsever, 2023). These methods were utilized to reduce the bias and variances of the forecasting error of component models (Oliveira and Torgo, 2015). For example, Ahmad et al. (2023) predicted unemployment rates in France, Spain, Belgium, Turkey, Italy, and Germany using a hybrid methodology combining the ARIMA and NNAR models. The findings revealed that the ARIMA-NNAR forecasting model demonstrated effectiveness for France, Belgium, Turkey, and Germany, while the hybrid ARIMA-SVM model performed well for Spain and Italy. Chakraborty et al. (2021) introduced a hybrid model (ARIMA-NNAR), assuming an additive connection between the linear and nonlinear elements of the time series, to forecast unemployment rates in Canada, Germany, Japan, the Netherlands, New Zealand, Sweden, and Switzerland. The findings indicated that their proposed hybrid models surpassed the individual ANN, ARIMA, NNAR, and SVM models for all countries. Moreover, they illustrated that their suggested model avoids displaying explosive variances over time and proves effective in capturing the asymmetry in unemployment rates. Moreover, Yurtsever (2023) forecasted the unemployment rate in France, Italy, the USA, and the UK using a hybrid approach combining long short-term memory (LSTM) and Gated Recurrent Unit (GRU). The results suggest that the hybrid model exhibited better performance across the four countries, except for Italy, where the GRU model yielded superior outcomes. A study conducted by Shi et al. (2022) explored the impact of the COVID-19 pandemic on forecasting the unemployment rate in seven developing countries in Asia (Bangladesh, China, India, Indonesia, Iran, Pakistan, and Sri Lanka) using time series, ANN, NNAR, SVM, and hybrid approaches. The findings revealed that ARIMA-NNAR outperformed individual ARIMA, ANN, NNAR, and SVM models, as well as hybrid ARIMA-ANN and ARIMA-SVM models.

In the context of the literature review above, the current research has identified gaps in the literature concerning the forecasting of the Palestinian unemployment rate, specifically in the context of NNAR models. While conventional univariate time series and ANN models have been widely applied globally, there is a shortage of studies focusing on Palestine and employing nonlinear forecasting methods. Furthermore, existing literature on accurate forecasting methods is inconclusive, with no single model accepted globally. The choice of the most suitable model is contingent on factors such as dataset characteristics, forecasting duration, geographical location, and data distribution (Galbraith and van Norden, 2019; Będowska-Sŏjka, 2015; Katris, 2020). The selection of the best method heavily dependent on factors such as spatial aspects and forecasting periods. To overcome these gaps, the study applies the NNAR methodology to quarterly Palestinian unemployment data, and assesses its effectiveness by comparing forecasting accuracy measures with conventional methods including SARIMA, HW's additive, and HW's multiplicative models. This study stands out from previous studies, as it highlights the usefulness for utilizing an NNAR model to predict unemployment rates in Palestine. It also contributes to the literature supporting the application of NNAR models in a similar context, in comparison to conventional linear time series and exponential smoothing methods.

3 Materials and Methods

The current study forecasts the Palestinian unemployment rate in the short run using the NNAR methodology. The choice to use the NNAR method for predicting the unemployment rate is based on its demonstrated superiority over classical time series models. Davidescu et al. (2021b) have stated that univariate NNAR models have been shown to produce higher accuracy and predictive performance, as compared to classical time series models. Unlike traditional methods, NNAR models are better suited to handling nonlinearity and non-stationarity in economic data, such as unemployment rate, making them appropriate for addressing the dynamic nature of unemployment rates. Furthermore, the NNAR methodology offers the distinct advantage of being less complex and more easily interpretable compared to other classical methods (Hyndman and Athanasopoulos, 2018). Hence, it is reasonable to anticipate that conventional forecasting techniques, including traditional linear and nonlinear time series methods, may produce inferior results in the context of unemployment rate forecasting. This expectation is based on the known limitations of classical approaches in capturing the complex dynamics and nonlinear relationships inherent in economic data, such as unemployment rates. This highlights the significance of employing NNAR methods in forecasting the unemployment rate, especially in economies characterized by higher volatility and uncertainty, such as Palestine.

The research strategy comprises three main steps for forecasting the Palestinian unemployment rate, namely understanding the dataset source and its characteristics; applying the NNAR model for forecasting methodology; and assessing forecasting accuracy. The third step involves comparing the forecasting accuracy of the NNAR model against SARIMA, HW's additive, and HW's multiplicative models to ensure the robustness of the results.

3.1 Unemployment Data

The unemployment rate is the primary indicator for measuring unemployment, representing the percentage of unemployed individuals within the labor force, according to ILO-modeled estimates. This study utilizes quarterly unemployment rate data for Palestine from 2001Q1 to 2023Q2, collected from the quarterly reports of the Palestinian Labor Force Survey (PLFS) and publicly available press releases from the Palestinian Central Bureau of Statistics (PCBS) database.

The descriptive statistics of the unemployment rate in Palestine are presented in Table 1. The average unemployment rate was 25.4% (SD = 2.9%). The highest unemployment rate was 35.6% (2002Q2). This surge could be attributed to the second Intifada, during which Israel imposed movement restrictions. In contrast, the lowest unemployment rate was 18.7% (2011Q2). Figure 1 illustrates the evolution of the Palestinian unemployment rate throughout the study period, revealing a nonstationary process.

Table 1: Descriptive statistics of the unemployment rate in Palestine (2001Q1 – 2023Q2)

Variable	Mean	SD	Median	Min	Max	Range
Unemployment rate, %	25.4	2.9	25.3	18.7	35.6	16.9

SD: Standard Deviation

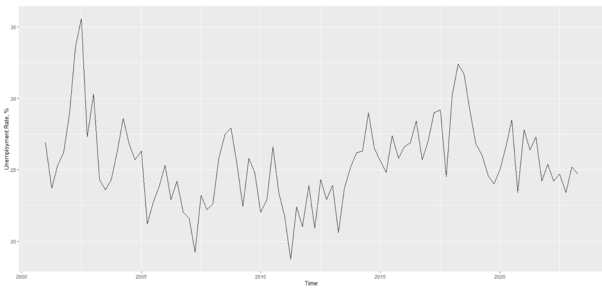

Figure 1: Time series plot of the Palestinian unemployment rate (2001Q-2023Q2)

Figure 2 illustrates that the Palestinian unemployment rate displayed seasonal variations throughout the study period, with peaks occurring during the third quarter of the year. This seasonal pattern is further confirmed by the autocorrelation function (ACF) plot shown in Figure 3. Additionally, the partial autocorrelation function (PACF) plot indicates that the quarterly Palestinian unemployment rate followed an autoregressive process of order 1; AR(1).

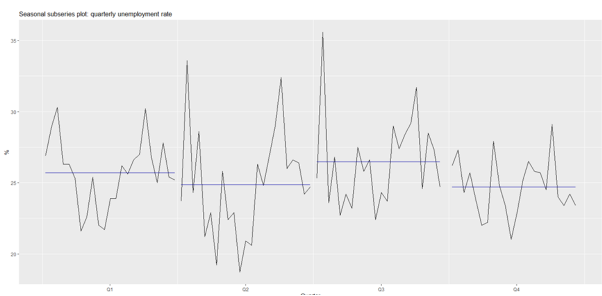

Figure 2: Seasonal trends in the quarterly unemployment rate in Palestine (2001Q1 – 2023Q2)

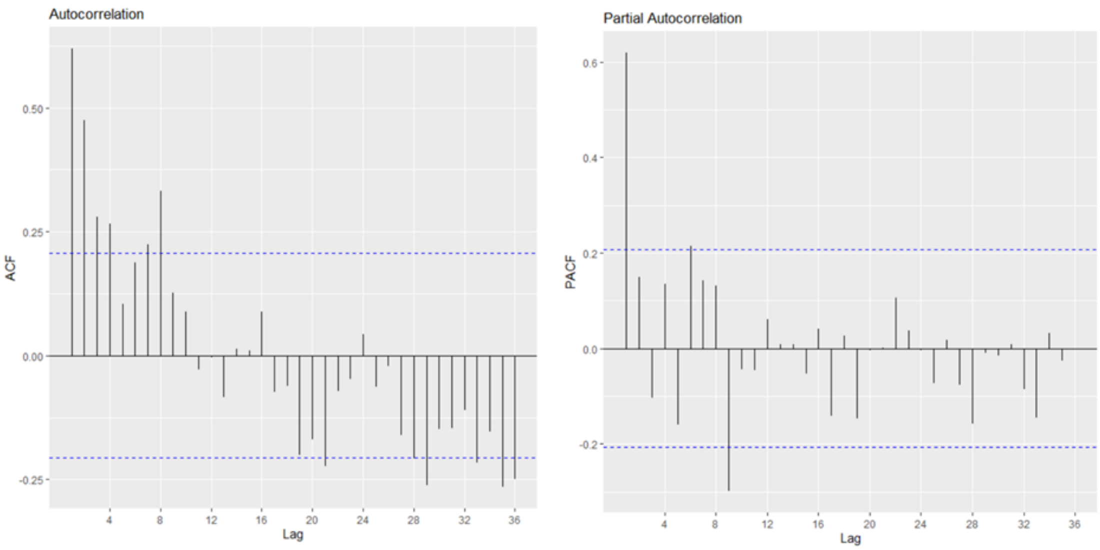

Figure 3: ACF and PACF plots of quarterly unemployment rate in Palestine (2001Q1 – 2023Q2)

In the context of time series forecasting, the dataset is divided into training and testing sets. The training set is utilized for in-sample forecasting, in which the model is trained. The testing set is used for out-of-sample forecasting and serves to evaluate the model's performance on new data not encountered during the training phase. A critical consideration in forecasting applications is the allocation of data for training and testing. In this study, 80% of the entire dataset constituted the training dataset, while the remaining 20% was allocated to the testing dataset (Hyndman and Athanasopoulos, 2018; Joseph, 2022).

3.2 Forecasting Method–NNAR

Artificial neural networks are employed and trained to model complex nonlinear relationships between input and output variables. The NNAR model uses lagged values of the time series as inputs to a neural network. However, it differs from the conventional linear forecasting method by relaxing the restriction of stationary in the time series. This model is denoted by NNAR(p, k), where p represents the number of lagged input variables and k represents the number of nodes in the hidden layer. It is a neural network model that uses the last p observations as inputs (y_{t-1},$y_{t-2}\ldots$, y_{t-p}) to forecast the output variable y_t with k neurons in the hidden layer (Ciaburro and Venkateswaran, 2017; Hyndman and Athanasopoulos, 2018).

In the case of seasonal data, the NNAR model uses the lagged values of the same season as inputs and its specification will be NNAR(p,P,k)$_m$, where P represents the number of seasonal lags. Therefore, the inputs of this model are the lagged values of time series and the lagged values of the same season (y_{t-1},y_{t-2},$\ldots$,y_{t-p},y_{t-m},$y_{t-2m}\cdots$,y_{t-Pm}) with k neurons in the hidden layer (Ciaburro and Venkateswaran, 2017; Hyndman and Athanasopoulos, 2018). Figure 4 shows the graphical representation of this model. Selecting the appropriate configuration for the hidden layer, which depends on the data, is crucial to prevent over-fitting. The choice of p helps determine the nonlinear auto-correlation structure of the series. Typically, the determination of the number of hidden layers and the number of nodes within each hidden layer must be completed before training. These values are typically chosen through cross-validation (Hyndman and Athanasopoulos, 2018).

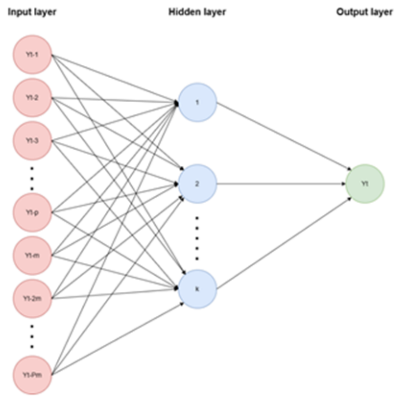

Figure 4: The diagram of the NNAR[p,P,k]$_m$ model

As illustrated in Figure 4, the NNAR mode is a multilayer feed-forward neural network in which every layer of nodes takes input from the preceding layers. In this network architecture, the outputs of nodes in a given layer serve as inputs to the subsequent layer. A weighted linear combination is employed to combine the inputs for each node. z_j is generated by linearly combining the inputs into hidden neuron j.

$$Z_j = \; b_j + \sum_{j=1}^{k} \; w_{ij}.y_i \tag{1}$$

In each hidden layer, the results obtained from Equation (1) are then modified by the nonlinear sigmoid function to generate the input for the subsequent layer.

$$s(z) = \frac{1}{\exp(-z)+1} \tag{2}$$

This transformation helps mitigate the impact of extreme input values, thereby enhancing the network's resilience to outliers. The parameters b_j and weights $w_(i,j)$ are trained and learned from the data. Initially, the weights are assigned random values, and subsequently, they are adjusted based on the available data. The results are averaged after training the network several times using different random starting points (Ciaburro and Venkateswaran, 2017; Hyndman and Athanasopoulos, 2018). In this study, the Palestinian unemployment rate exhibited seasonality in the data ($m = 4$), and its lagged values for the same season will be included as input variables. Hence, the model will be presented as NNAR[p,P,k]$_4$.

The estimation of parameters involves selecting those that minimize the accuracy metrics, and the model's performance is assessed using out-of-sample predictions. The neural network makes forecasts iteratively, or one step at a time. Therefore, when making multiple-step forecasts, the initial forecast is used as the subsequent input in combination with the historical data, until all forecasts have been generated (Ciaburro and Venkateswaran, 2017; Hyndman and Athanasopoulos, 2018).

Model diagnostics play a crucial role in forecasting applications and are typically carried out through residual analysis. The examination of residuals from a fitted model is of particular importance. These residuals should exhibit the characteristics of white noise, which include normal distribution with a mean of zero, constant variance, and the absence of serial autocorrelation (Ciaburro and Venkateswaran, 2017; Hyndman and Athanasopoulos, 2018).

3.3 Forecasting accuracy

Forecasting accuracy serves as a benchmark for evaluating the performance of forecasting models, and assesses the effectiveness of a forecasting model in predicting future values. To assess the accuracy of forecasts, it is essential to evaluate the performance of a model using new data that were not utilized during the model's training process. Therefore, a model is fitted using the training dataset to estimate its parameters, then assessed for its forecasting accuracy using the testing dataset. The subsequent step is to forecast the future values of the time series (Ciaburro and Venkateswaran, 2017; Hyndman and Athanasopoulos, 2018).

Forecasting accuracy is captured using different measures, including scale-dependent errors, percentage errors, and scaled errors. Scale-dependent errors include RMSE and MAE. Percentage errors are assessed using MAPE, while scaled errors include MASE. A smaller value for these error statistics indicates better forecast performance for the model (Ciaburro and Venkateswaran, 2017; Hyndman and Athanasopoulos, 2018; Kožuch et al., 2023).

Suppose y_{t+h} represents the forecast h steps ahead of y_{t+h}, the associated forecast error can be defined as $e_{t+h} = y_{t+h} - \hat{y}_{t+h|t}$. Subsequently, the evaluation statistics for forecasting performance, relying on N number of h-step ahead predictions, can be formulated as follows:

$$MAE = \frac{1}{N}\sum_{j=t+1}^{t+N} |e_{j+h|j}| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=t+1}^{t+N} (e_{j+h|j})^2} \tag{4}$$

$$MAPE = \frac{1}{N}\sum_{j=t+1}^{t+N} |\frac{e_{j+h|j}}{y_{j+h}}| \tag{5}$$

$$MASE = \frac{1}{N} | \frac{e_j}{\frac{1}{N-m} \sum_{t=m+1}^{N} |y_t - y_{t-1}|} | \quad (6)$$

To evaluate the reliability of the forecasting results, the current study compared the estimated NNAR model with certain classical time series forecasting models, including SARIMA, HW's additive, and HW's multiplicative methods.

4 Results and Discussion

The Palestinian unemployment rate dataset has been divided into training and testing sets. The training dataset covers the period 2001Q1 – 2017Q4, while the testing dataset covers the period 2018Q1 – 2023Q2. The graphical representation of the ACF and PACF of the original series of the unemployment rate in Palestine exhibits an autoregressive pattern of order 1; AR(1). Additionally, the number of seasonal lags is set at a value of 1 since there is seasonality in the data, as shown previously in Figure 3 (Davidescu et al., 2021b). Therefore, this study assesses the unemployment rate in Palestine using NNAR$[1,1,k]_4$. The NNAR model is estimated to identify the optimal value of k, whereby the accuracy of in-sample and out-sample forecasts is assessed using RMSE, MAE, MAPE, and MASE. The findings suggest that the optimal value of k is 10 nodes in the hidden layer, using both in-sample and out-of-sample forecasts. Hence, this study reveals that the NNAR$[1,1,10]_4$ model is the optimal model for predicting the unemployment rate in Palestine. Table 2 shows the values of forecasting accuracy measures for the optimal k = 10. Therefore, the Palestinian unemployment rate exhibits non-stationary, nonlinear, and seasonal behavior over the study period. The identified model is comparable to the proposed NNAR model used to model the Romanian monthly unemployment rate (Davidescu et al., 2021b).

Table 2: Forecasting Performance of the NNAR$[1,1,10]_4$ model

Accuracy Measure	Training dataset	Testing dataset
MAE	0.975	1.431
MAPE	3.384	5.494
MASE	0.352	0.516
RMSE	1.260	1.782

Furthermore, selecting the best NNAR model depends on the performance of the residuals, which involves checking model assumptions, including normality and serial autocorrelation of the residuals. The results of the Ljung-Box test indicate that the p-values associated with the test statistic exceed the 5% significance level for all lag orders, as displayed in Table 3. This suggests that there is no statistically significant autocorrelation observed in the residuals. This result has been confirmed by the ACF plot in Figure 5. Furthermore, the normal probability plot shows that the residuals are approximately normally distributed, as displayed in Figure 5 and confirmed by the

Shapiro-Wilk test (p-value = 0.4572 > 0.05). Therefore, the model passes all diagnostic tests for the best model fit, and residual errors are white noise. This study also assesses

Table 3: Residuals diagnostics using Ljung-Box test

Lag	Ljung-Box	p-value
4	2.764	0.598
8	6.547	0.586
12	9.728	0.640
16	11.232	0.795
20	14.416	0.809
24	15.656	0.900
28	19.155	0.893

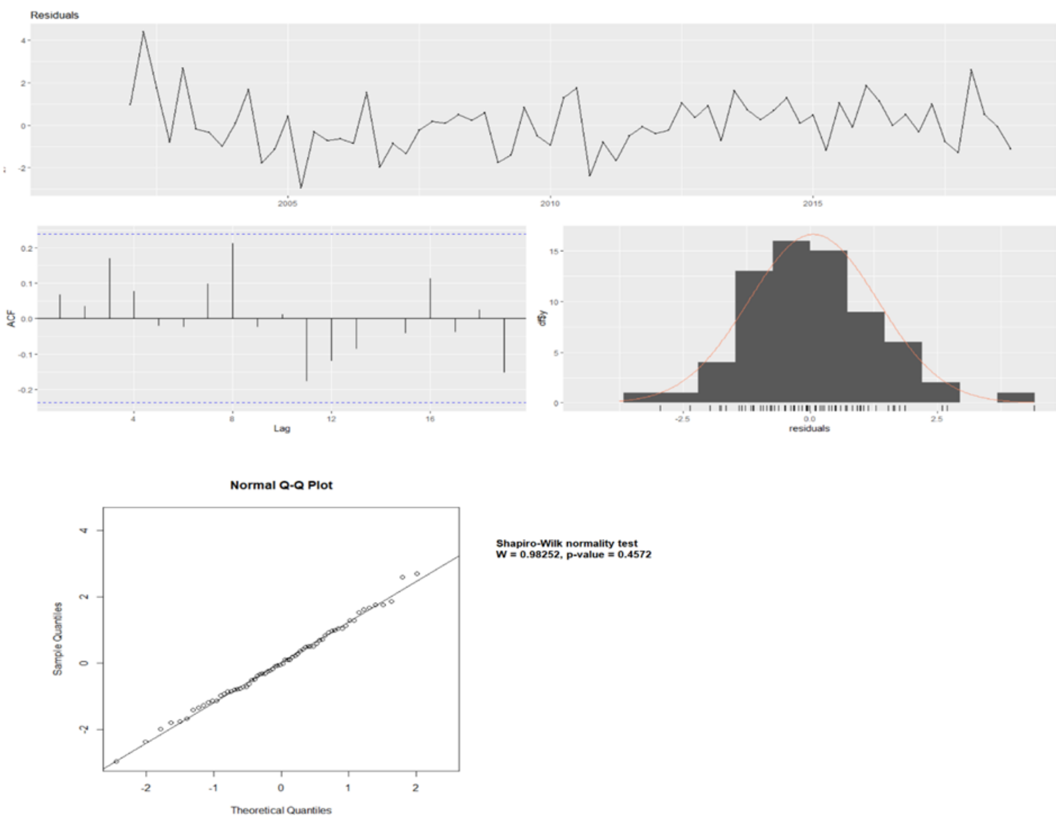

Figure 5: Residuals diagnostic plots for the NNAR[1,1,10]m model

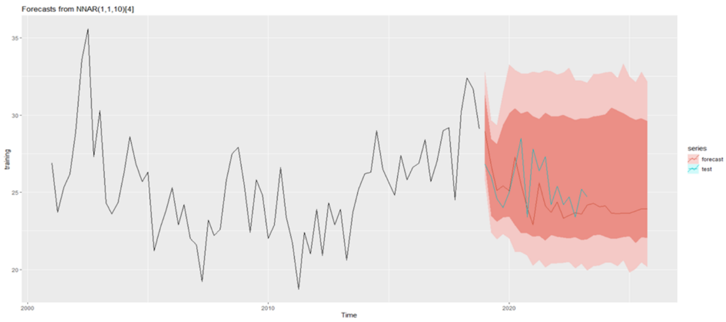

Figure 6: Predictions for the unemployment rate using the NNAR$[1,1,10]_m$ model

the forecasting accuracy of the estimated NNAR model by comparing the predicted values with actual values in both in-sample and out-of-sample forecasts. The findings reveal that the predicted figures of the unemployment rate do not deviate significantly from the testing dataset, as displayed in Figure 6. Therefore, the estimated model has performed well in terms of forecasting accuracy.

To assess the reliability of the estimated results, we compared forecasting accuracy measures with three classical forecasting methods, namely SARIMA, HW's additive, and HW's multiplicative models. Specifically, we forecasted the unemployment rate using these methods, comparing the accuracy measure values with our NNAR$[1,1,10]_4$ model. Table 4 illustrates that the forecasting accuracy measures (MAE, MAPE, MASE, and RMSE) of the NNAR model are lower than that of other conventional methods. This study has demonstrated the effectiveness of NNAR in forecasting the Palestinian unemployment rate, outperforming HW's additive, HW's multiplicative, and SARIMA models.The findings of this study demonstrate both similarities and differences when compared to previous studies forecasting unemployment rates using classical time series and NNAR methods. This finding aligns with a study conducted by Davidescu et al. (2021b), illustrating that the NNAR model outperformed ETS, HW's additive, HW's multiplicative, SARIMA, and SETAR models for modeling the Romanian monthly unemployment rate. However, Mahipan et al. (2013) have shown that the SARIMA$(0, 1, 1)_{12}$ model outperforms ANN models for forecasting the unemployment rate in Thailand, which contradicts our findings. Meanwhile, Yamacli and Yamacli (2023) have shown that ANN models perform well during economic uncertainty, while the ARMA model performs better in normal situations in the Turkish labor market. In contrast, Gostkowski and Rokicki (2021) showed that HW's multiplicative and quadratic regression methods offered better forecasting performance of the Polish unemployment rate. Therefore, our findings are consistent with a growing body of literature that supports the use of NNAR models in forecasting economic indicators such as unemployment rates. By replicating and extending these findings in the context of the Palestinian unemployment rate, our study further supports the consensus that NNAR models offer a more effective approach to short-term forecasting in volatile and dynamic economic environments.

Although this study has not considered hybrid approaches, the results of previous

Table 4: Forecasting accuracy measures using the conventional methods

	HW' Additive Model		HW' Multiplicative Model		SARIMA Model	
Measure	Training	Testing	Training	Testing	Training	Testing
MAE	1.787	5.023	1.785	5.894	2.001	3.352
MAPE	7.071	20.077	7.131	23.492	7.945	13.350
MASE	0.645	1.182	0.644	2.126	0.722	1.209
RMSE	2.263	5.232	2.355	6.094	2.432	3.653

Note: the order of SARIMA model was $ARIMA(1, 1, 1)(0, 1, 1)_4$.

studies which developed hybrid approaches have shown that the hybrid model ARIMA-NNAR outperformed individual ANN, NNAR, and ARIMA models (Ahmad et al., 2023; Chakraborty et al., 2021; Shi et al., 2022). Conversely, Katris (2020) concluded that there is no universally accepted single model for forecasting the unemployment rate across all countries worldwide. This emphasizes the need for further investigations in the Palestinian context.

Table 5 presents the short-term predictions of the quarterly unemployment rate in Palestine for the next 10 quarters, covering the period from 2023Q3 to 2025Q4. The findings indicate that the predicted Palestinian unemployment rate in the third quarter of 2023 was 27.2%, compared to 24.7% in the second quarter of 2023. This rate is expected to increase in the short run, and over the entire forecasting period, it fluctuates between 23.8% and 28.1%, demonstrating a strong pattern of nonlinearity and seasonality (see Figure 6). Nevertheless, a press release by PCBS (2023) reported that the Palestinian unemployment rate increased from 25.5% in 2022 to 30.7% in 2023, closely aligning with our forecasted values. The press release also suggests that, due to the Israeli aggression on the Gaza Strip and its repercussions on Palestine, the unemployment rate is anticipated to reach 46.0%. Given the asymmetry in the Palestinian labor market, future research is needed to model this economic instability.

5 Conclusion and Policy Implications

5.1 Conclusion

The unemployment rate is considered a reliable indicator of a country's labor market conditions and is essential for measuring its economic performance. It proves useful for making informed investment decisions for financial market participants, in addition to benefiting central banks in establishing monetary policies to reduce unemployment. Unemployment also typically has adverse social consequences for individual well-being. Therefore, accurate forecasting of the unemployment rate is essential for targeted social and financial policies. The current study attempts to implement the NNAR model to predict the short-term behavior of the Palestinian unemployment rate and sheds light on its usefulness. Various investigative findings align with both theory and data. First, the

Table 5: Forecasted unemployment rate in Palestine (2023Q3 – 2025Q4)

Year (Quarter)	Forecast based on NNAR$(1,1,10)_4$
2023 (Q3)	27.2%
2023 (Q4)	26.6%
2024 (Q1)	28.1%
2024 (Q2)	25.3%
2024 (Q3)	27.0%
2024 (Q4)	26.2%
2025 (Q1)	25.1%
2025 (Q2)	23.8%
2025 (Q3)	25.7%
2025 (Q4)	25.3%

Palestinian unemployment rate has exhibited a nonstationary nonlinear pattern over the past few decades, and has asymmetries due to economic and political instability. Second, the suggested NNAR model shows improved forecasting accuracy and promising results compared to traditional methods. Finally, the current study aligns with the increasing body of research supporting the application of NNAR models in predicting unemployment rates, as compared to traditional time series models.

5.2 Policy Implications

The findings of this study indicate that the Palestinian unemployment rate is expected to remain a chronic problem, posing significant challenges for policymakers in shaping economic policies in Palestine. The economic implications of a sustained and high unemployment rate suggest weak demand in the Palestinian economy, indicating a reduced need for workers, which may lead to decreased working hours or layoffs. This situation has led to lower worker and social income, exacerbated income inequality, and contributed to rising poverty and social instability (Yurtsever, 2023). Furthermore, elevated unemployment rates have the potential to impact overall economic productivity and capacity (Crowder and Smallwood, 2019). A study by Samarah (2021) revealed that a 1 percent increase in the unemployment rate resulted in a 0.356 percent reduction in GDP per capita in Palestine.

The findings of this study open doors for the government and decision-makers to implement policies and strategies that maintain individual welfare and the country's development. One major policy involves ensuring that unemployed individuals are securing sustainable employment opportunities and receiving necessary social support. Furthermore, the accurate forecasting presented in this study may guide the Palestinian

Monetary Authority (PMA) in establishing monetary policies to reduce the unemployment rate, such as decreasing the interest rate. Moreover, the unemployment rate could indirectly affect the financial market and stock returns, since this indicator is mainly related to labor market conditions and changes in the business cycle and monetary policy. Therefore, the findings will be useful for investors to avoid market dangers arising from unexpected changes in economic conditions and monetary policies.

5.3 Limitations and Future Recommendations

Despite the promising results emerging from this study, it has several limitations. The study implements univariate forecasting methods and does not consider certain controlling factors and macroeconomic determinants of unemployment. To enhance the reliability of results, future studies should incorporate crucial factors affecting unemployment, such as the inflation rate, gross domestic product, interest rate, and the percentage of tertiary education (Hossain et al., 2018; Stasinakis et al., 2016; Yamacli and Yamacli, 2023). An extension of this research will be conducted to evaluate the forecasting performance of the model using different approaches, including univariate, hybrid, and multivariate models.

Furthermore, this study has not accounted for spatial and gender differences in the unemployment rate in Palestine. Substantial variations exist based on gender and geographic areas (e.g., West Bank and Gaza Strip). Therefore, future research should aim to forecast the unemployment rate separately for men and women, as well as for the West Bank and Gaza Strip. This approach will provide valuable insights for policymakers in developing targeted social and monetary policies.

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