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Forecasting Senegalese quarterly GDP per capita using recurrent neural network

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Abstract

This article evaluates the predictive efficiency of RNNs comparing two types of architecture on quarterly GDP per capita data from Senegal over the period 1960-2020, namely a recursive neural network with re-estimation and a recursive neural network without re- estimate. The RMSE, MAPE and MAE values of the chosen neural network are respectively 7.41%, 8% and 7.73% lower than those of the RNN model has one hidden layer without re-estimation. Indeed, the architecture with two hidden layers converges less quickly than that with only one hidden layer. Thus, the one hidden layer RNN with re-estimate remains the best forecast of Senegal's quarterly GDP per capita during the test period considered. These results suggest the use of artificial neural networks for forecasting economic variables.

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1. Introduction

The gross domestic product (GDP) remains one of the most fundamental economic indicators. Indeed, it constitutes an important reference for the elaboration of the State's economic policy and the consumption, saving and investment plans of households and companies. Its evolution is therefore the subject of great attention from all economic actors, despite its shortcomings noted by many authors including Stiglitz et al (2009).

Several methods for forecasting GDP and its evolution are available. Among the traditional statistical models, the Autoregressive Integrated Moving Average (ARIMA) model remains one of the most used in the literature (Sunitha et al., 2018). Artificial Neural Network based forecasting techniques including Recurrent Neural Network (RNN) are among the most successful new forecasting tools for nonlinear and nonparametric data (Petnehâzi, 2019).

Chuku et al (2019) compared "the forecasting performance of artificial neural networks (and those of) Box-Jenkins and structural econometric modelling applied to forecasting economic time series in African economies" using different forecasting performance measures. Overall, their results for GDP growth forecasting show that Neural Network models "perform somewhat better than structural econometric and ARIMA models," especially when relevant variables such as commodity prices and interest rates are used as input variables.

On the other hand, Olaniyi et al (2014), using five performance measures, demonstrated the clear superiority of ANN over multiple regression analysis, in terms of stock market prediction efficiency. They were indeed interested in the relationship between the stock market and economic growth in Nigeria, by comparing two forecasting methods, an ANN and multiple regression analysis and using quarterly data from 1990 to 2009.

Analyzing the root mean square error (RMSE) and mean absolute percentage error (MAPE) values for forecasting India's GDP growth over the period 1951-2016, Sunitha et al. (2018) found that the artificial neural network multilayer perception model outperforms the autoregressive integrated moving average (ARIMA).

Based on the results of these works, the use of RNN for forecasting becomes legitimate. Thus, we question the predictive efficiency of RNN based on quarterly GDP per capita data for Senegal over the period 1960-2020. This paper aims to assess the effectiveness of the techniques for forecasting Senegal's quarterly GDP per capita (GDPt/h) using RNN. The hypothesis adopted is that neural network models of Senegalese GDPt/h with a reduced number of hidden layers give better accuracy. The justification lies in the fact that most of the works encountered, including those of Moody (2012) and Uzair et al (2020), conclude that neural network models with a smaller number of intermediate layers give better forecasting accuracy.

The interest in using RNNs to forecast GDP is growing, as evidenced by the work on many countries including the United States, Germany and China. However, we note the absence of studies for French-speaking sub-Saharan countries, including Senegal, which use quasi-accounting models to forecast GDP. This paper thus contributes to the range of forecasting tools for economic indicators used at the national level and more generally at the West African region level.

Unlike authors who use GDP-determining variables such as population growth rate, inflation, and political stability (Liliana and Napitupulu, 2012), we use only past GDP data to forecast Senegal's GDPt/h.

For the rest of the article, section 2 proposes a synthetic review of the literature. Section 3 explains the methodology adopted. Section 4 presents and analyzes the forecasting results. Section 5 is devoted to the conclusion.

2. Literature review

Since the second half of the 1990s, several works based on neural network models have been carried out to forecast macroeconomic variables, especially GDP growth. Based on an applied study, Petnehâzi (2019) shows that the neural network models are more flexible and better for forecasting time series data than the usual linear models. This result corroborates that of Thiesing and Vornberger (1997) who had asserted the better prediction quality of RNN relative to conventional techniques, namely naive prediction and statistical prediction[1].

After explaining the constraints and limitations of time series models-short data runs, high noise levels, non-stationarity, and non-linear effects-Moody (2012) proposes to forecast the U.S. industrial production index using several methods. His empirical results show the superiority of state-of-the-art neural network models over regression and time series methods.

In contrast to the traditional econometric approach, the neural network technique has, according to Junoh (2004), enormous potential for predicting GDP growth based on economic indicators. Jahn (2020) showed that for predicting annual GDP for 15 industrialized economies, an ANN model performed better than a linear model.

For Liliana and Napitupulu (2012), the ANN is a relatively better forecasting tool for GDP growth than the one used by the Indonesian government. The ANN model performs better than the dynamic factor model in terms of forecasting US quarterly GDP but offers as good current forecasts as the Survey of Professional Forecasters (Loermann and Maas, 2019).

Two groups of authors have also used artificial neural networks with a back-propagation learning algorithm to forecast GDP per capita. The first group, Zhang et al. (2022), consider that this stochastic learning method remains a useful complement to existing methods and facilitates policymakers to develop "quick and effective macro-control plans based on the predicted GDP trend" of the Shandong region. The second group, Abdullah Erdal and Aytekin (2018), investigated the predictability of GDP per capita by developing different architectures and using data from what they describe as non-economic variables such as education level and the percentage of research and development expenditure in GDP.

Believing that artificial neural network models perform better than statistical methods in terms of forecasting accuracy, Jena et al. (2020) used a multilayer artificial neural network model to analyze the impact of COVID-19 on the GDP of major economies - the United States, Mexico, Germany,

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[1] For a detailed review of RNN for forecasting, one can refer to Hewamalage et al [2021]. Also Gamboa [2017]provides a more recent review of deep learning applications to time series data

Italy, Spain, France, India, and Japan. The main result reveals that multilayer artificial neural network models have higher forecasting accuracy than statistical methods.

Longo et al (2021) use a combination of artificial neural networks and a dynamic factor model to forecast U.S. GDP. They show that their model satisfactorily reflects the evolution of the business cycle[2].

Ultimately, this selective literature demonstrates the usefulness and importance of neural networks as an innovative and powerful predictive tool, especially for forecasting macroeconomic variables such as GDP per capita. This literature thus justifies the choice of RNN, which are more specific, to forecast time series such as Senegal's GDPt/h.

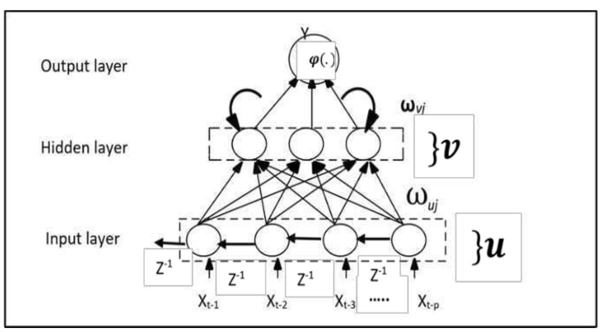
3. Methodology

The methodological approach is divided into two parts. First, the preferred forecasting models are presented. Then, the performance measures of the forecasts will be explained.

3.1 Preferred forecasting models

RNN remain the most appropriate type of neural network for time series forecasting. Unlike other types of neural networks, the one that is the subject of our article is said to be recursive because it allows the recursive integration of past and present information through appropriate transfer functions. A good design of the architecture of a RNN as shown in figure 1 is not only crucial for the realization of a robust learning system but also allows highlighting how the information flows between different neurons. Here the RNN is applied on time series data of GDP per capita x(t) to get its predictions Y(t). The input nodes are the previous lagged observations while the output provides the prediction of the future value. The main idea behind recurrent neural networks is to use not only the input data but also the previous outputs to make the current prediction.

Figure 1: Recurrent Neural Network (RNN)



This architecture contains three types of nodes namely input nodes, hidden or intermediate nodes and output nodes. Here only the hidden nodes have both inbound and outbound connections

The input nodes are devoid of incoming connection as well as the output nodes are devoid of outgoing connection. For each neuron i, i = 1, 2,... N, the elements j = 1, 2,..., M, of a neuron's

[2] However, the authors also used several other interesting GDP forecasting models. For example, Abdié et al. (2020) instead used a factor model to forecast quarterly GDP for Bosnia and Herzegovina. Zhemkov (2021) relies on a combination of forecasts to predict Russia's GDP and the growth rates of its components by expenditure in the short run.

input vector are weighted and then summed to produce a neuron's internal activation function v. This is then fed into another non-linear activation function $\varphi(.)$ commonly referred the transfer function, to form the output of our prediction yi. This activation function links and connects nodes of the same layer. It is given by:

$$\tanh(v) = \frac{e^{v} - e^{-v}}{e^{v} + e^{-v}} \quad (1)$$

Z-1 represents the time shift operator between a source and a destination node.

$$v(t) = \sum_{j=1}^{M} \omega_{u,j}(t)u(t-j) + \sum_{i=1}^{N} \omega_{v,i}(t)v(t-i) \quad (2)$$

$$y(t) = \varphi\big(v(t)\big) \quad (3)$$

With $\omega_{u,j}$ is the weight associated with the input delay, $\omega_{v,i}$ equal to the weights associated with x and v. M and N represent respectively the number of input nodes and the number of hidden nodes.

3.2 Forecasting performance measures

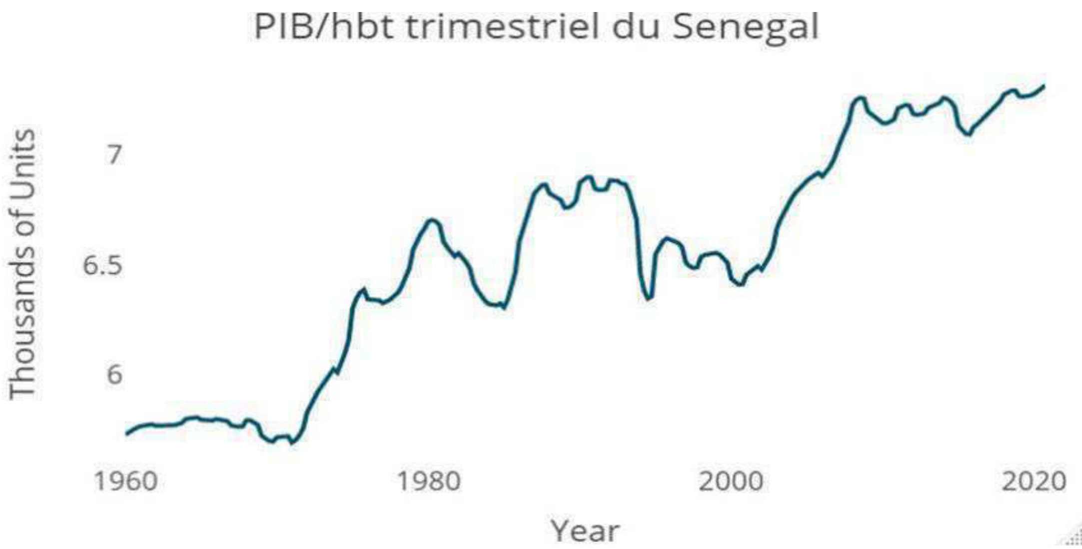
The choice of error measures should be based on a good knowledge of their statistical properties and the nature of the data used (Davydenko et al., 2016). Following the example of Greg,T. (2001), we use four measures with different characteristics. However, when evaluating the relative performance of different prediction methods on the same predictive task, error-based computation of measures is very often used in the literature. Here we are interested in the roots mean square error (RMSE), the mean absolute percentage error (MAPE), the mean absolute error (MAE) and finally the correlation coefficient between predicted and actual values (see appendices). When comparing the accuracy of different predictions, it is necessary to clarify whether the units of the original data of different predictions are the same or not, and whether the scales of the original data are the same or not (Jierula; Wang; OH; Wang 2021).

The annual GDP data come from World Development Indicators (World Bank, 2022) and cover the longest possible period, 1960-2020. Since quarterly data are not available on official Senegalese statistical sites, we have transformed the data from annual to quarter with the so-called Denton method using the Eviews software. This method is based on the principle of preserving fluctuations and considers a loss function in quadratic form between the original and adjusted series. We end up with 244 observations, or 61 quarters.

4. Presentation and analysis of results

It is important to analyse the main trends in the evolution of quarterly GDP per capita before moving on to forecasts. Figure 2 below shows a highly fluctuating trend in Senegal's quarterly GDP per capita over the period studied.

Figure 2: Evolution of Senegal's quarterly GDP per capita



Four main evolution's stages can be broadly identified here. The first phase is characterized by a slight increase in quarterly GDP per capita from 1960 to the early 1970s. The second phase is marked, despite the drought of the mid-1970s, by a steady increase in quarterly GDP per capita over the decade 1970-1980 with a slight drop at the end of the period, due to the fall in commodity prices. The third phase, from the beginning of the 1980s to the beginning of the 2000s, corresponds to a very fluctuating, jagged evolution. The implementation of structural adjustment policies in the early 1980s had a negative impact on the evolution of quarterly GDP per capita. The fourth phase has an overall upward trend due to expansionary fiscal policies. Public spending on airport, road and rail infrastructure had indeed positive effects on Senegal's economic growth. This latest phase consists of two sub-periods. In the first, quarterly GDP per capita s growing steadily enough to peak in 2015. The second sub-period, from 2016 to 2020, is characterized by very small variations and remains relatively stationary.

4.1 Recurrent Neural Network

The results were obtained by dividing our database into two subsets. The first subset, called training, goes from the first observation to the T^{ieme} observation in which the modeling and the tuning of the model take place. The second subset, called testing set, corresponds to the time interval T+1 and T+i in which the forecasting takes place. All data were standardized before being modeled by the back propagation recurrent neural network algorithm.

Two types of RNN were implemented in this study: one with re-estimation after each new observation and one without re-estimation. The results of the model's group without re-estimation are given in Tables I and II. Table I shows a model with an input layer, and one hidden layer in which the number of neurons has been varied from 3 to 10 and finally an output layer whose number of neurons is set at 1. Table II shows the two hidden layer model's result. Within this model, the number of neurons in the second hidden layer was also varied between 3 and 10. It has been observed (see Figure 6.a in annexes) that architecture with two hidden layers converges less quickly than architecture with only one hidden layer. The number of iterations of all models is set at 1000.

During this training phase, we will use the Leveng Marquardt back propagation algorithm. This allowed us to obtain a weighted matrix that will be applied to our testing set for forecasting purposes.

The model fit's quality is tested during the training phase and it performance was examined. Equations (4), (5), (6) and (7) are applied to observed data and forecast data to assess the quality of the forecast.

The results of the two models, without re-estimation with one layer and without re-estimation with two layers, are respectively exposed and commented below.

Table I. One hidden layers model without re-estimation

NUMBER OF NODE	R-Training	R-Test	RMSE	MAPE	MAE
3	0.9856	0.9687	0.1464	0.1485	0.1356
4	0.9889	0.9650	0.1469	0.1482	0.1360
5	0.9871	0.9778	0.1410	0.1429	0.1308
6	0.9878	0.9759	0.1425	0.1430	0.1314
7	0.9885	0.9809	0.1460	0.1462	0.1345
8	***0.9892***	0.9803	0.1391	0.1396	0.1283
9	0.9891	0.9829	0.1317	0.1335	0.1222
10	***0.9879***	***0.9638***	***0.1253***	***0.1270***	***0.1163***

Figures 3: One hidden layers model training set and testing set

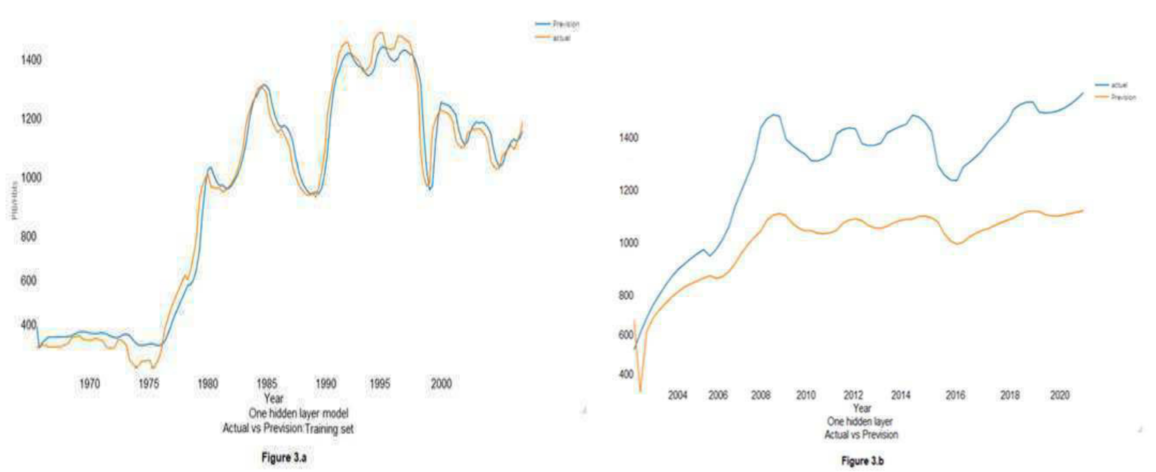


Table I reports the predictive performance of the different models with a hidden layer by comparing RMSE, MAPE and MAE measures. Eight models were studied with different parameters. The correlation coefficient of the model in the training set is around 98% compared to 96.38% in the test set. This strong correlation noted in Table I is confirmed in Figure2.a which could suggest a situation of over-fitting of the model in the training sample.

However, Figure 6.a which shows a sharp drop in the error at 33rd iteration before gradually stabilizing, confirms the absence of overfitting during the training phase. The model with 10-node appears to be the most efficient with RSMA, MAPE and MAE equal to 0.1253, 0.1270 0.1163 respectively. Figure 2.b above shows the evolution of the predictions in the testing sample.

Table II. Two hidden layers model without re-estimation

NUMBER OF NODE	HIDDEN LAYERS	R-Training	R-Test	RMSE	MAPE	MAE
5	(2,3)	0.9864	0.7329	0.1793	0.1844	0.1657
6	(2,4)	0.9887	0.7974	0.1635	0.1646	0.1510
7	(2,5)	0.9838	0.7412	0.1729	0.1781	0.1586
8	(2,6)	0.9856	0.7431	0.1673	0.1710	0.1530
9	(2,7)	0.9854	0.7387	0.1941	0.2042	0.1814
10	(2,8)	0.9860	0.6770	0.1614	0.1636	0.1456
11	(2,9)	0.9849	0.6565	0.1692	0.1709	0.1531
12	***(2,10)***	***0.9851***	0.7071	***0.1635***	***0.1335***	***0.1467***

Figures 4: Two hidden layers model: training set and testing set

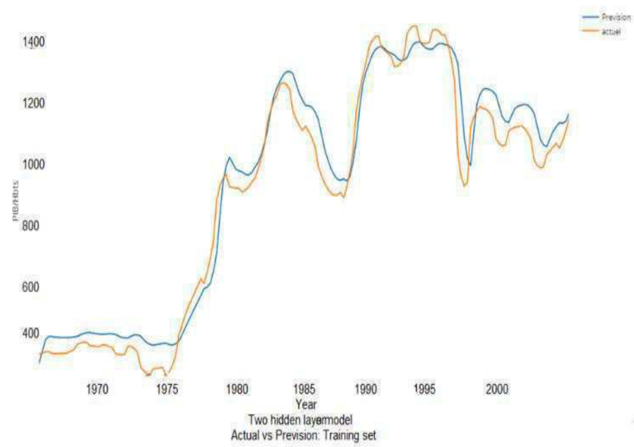


Figure 4.a

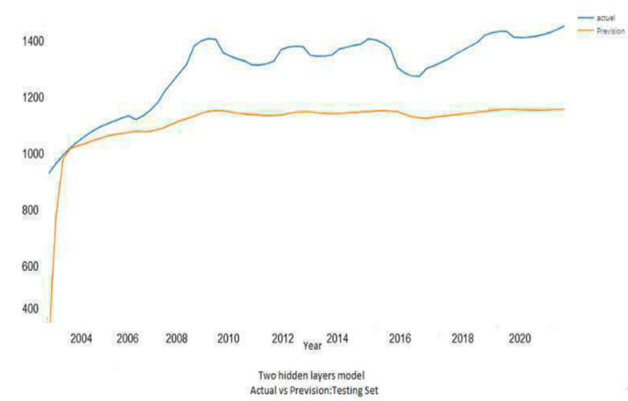


Figure 4.b

Table II shows that we repeatedly ran our model by fixing the first hidden layer to two and varying our second hidden layer in order to optimize our models presented in Table I. These models do not converge as fast as simple architecture models. Like the results presented in Table I, the model with 12 neurons in total, i.e. 2 neurons in the first layer and 10 neurons in the second layer, remains the most efficient by its performance measures such as RMSE (0.1635), MAPE (0.1335), and MAE (0.1467).

Although the correlation coefficient remains unstable throughout the variation of the number of neurons, the accuracy of the performance measures increases. The correlation coefficient of the best RNN model (2.10) in the test sample is low (70.71%) compared to the 0.9638 of the one hidden layer model (Table I). The comparison of figures 3b and 4b above shows that the prediction of the one-layer model better reflects the evolution of Senegalese GDP per capita in the test sample.

The explanation of the two forecasting models allows us to compare their performance based on measures of the correlation coefficient R, RMSE, MAPE and MAE.

4.2 Model Comparison

In this section, we present the results of our prediction comparison. The reported results are for the final network architectures, as indicated in the previous results. Table III below presents the results of the performance metrics for the two selected prediction models.

Table III. Comparison of forecasting models

MODELE	ARCHITECTURE	R	RMSE	MAPE	MAE
RNN with re-estimation	10 nods 1 layer	0.99064	0.0512	0.0474	0.0390
RNN with re-estimation	C(2,10) 2 layer	0.98927	0.3107	0.2692	0.2342

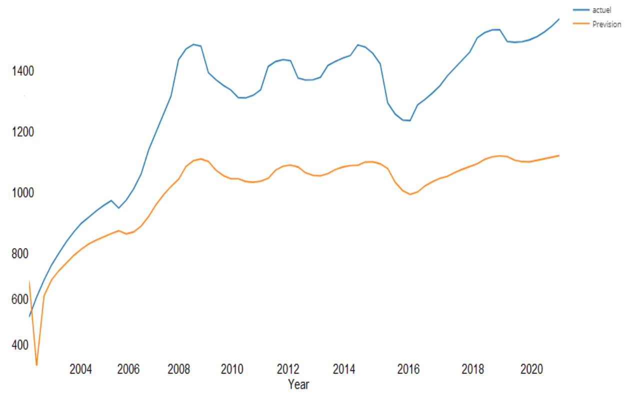
Table III reports the out-of-sample performance for both models. The RMSE, the MAPE and the MAE evaluate the accuracy of the forecasts. The results are reported for each of the models, for the periods to come. The maximum forecast horizon is therefore 3 years, or 18 quart

We begin by presenting the results of the validation period before turning to the test period. For each period, we first report the forecast accuracy as measured by our evaluation methods. These measures are negatively oriented, so that a lower value indicates a higher forecast accuracy. We then compare the two studied architectures against each other.

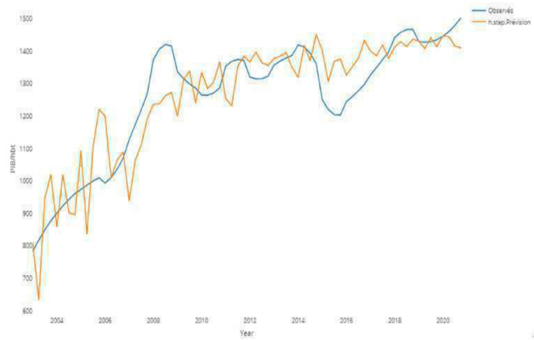
Overall, the one hidden layer RNN with re-estimation remains the best method for forecasting Senegal's quarterly GDP per capita during the test period. Indeed, the one-layer RNN records the best performance when it comes to RMSE, MAPE and MAE that are 0.051; 0.047; and 0.039 respectively. It outperform the two hidden layer architecture with re-estimation by 26% (0.3107-0.0512) in terms of RMSE, by 22.17% in terms of MAPE and by 19.5% in terms of MAE. As in most studies, Walczak (2001, p. 211) found that single-hidden-layer neural networks consistently outperformed two hidden layer neural networks and were able to reach the 60% accuracy threshold.

Table II shows that even if the single hidden layer architecture appears to be the best model in terms of forecasting extremes, it is not the most robust in terms of its MAE. Indeed, a lower relative RMSE indicates that the approach is better at predicting extremes cases, while a higher relative MAE indicates that the approach is more robust.

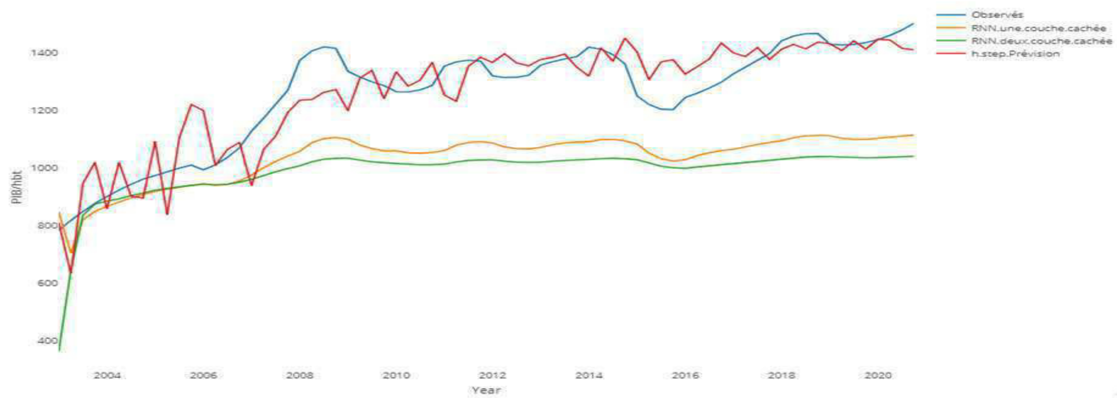
Figures 5: Actual vs. Forecast for both models



Ttraining set:One hidden layer without re-estimation



Testing set: One hidden layer with re-estimation



Senegalese quarterly GDP per capita: model's comparison

Examination of Figure 5 shows that RNNs are able to model seasonality directly if the dataset series have homogeneous seasonal patterns and provide significant improvements in forecasting. The gains in forecast accuracy appear to come from the ability of RNNs to capture non-linear phenomena.

Ultimately, the NNR models reveal a very high level of correlation between predicted and actual values of quarterly GDP per capita (Figure 5 above). Indeed, Figure 6 confirms this finding. More precisely, they indicate that the predictions of the final model chosen, the RNN with one hidden layer, fit the data perfectly both in the training and in the test. They thus reinforce graphically the results of Table III.

5. Conclusion

In this article, we assessed the predictive effectiveness of RNN using quarterly GDP per capita data for Senegal over the period 1960-2020. The RMSE, the MAPE and the MAE evaluate the performance, designating the precision of the forecasts.

The results of the two models – two final RNN network architectures – reveal that the RNN has one layer with re-estimation remains the best method for forecasting the quarterly GDP per capita of Senegal during the test period considered. These results validate the hypothesis and corroborate more empirical work mentioned in the literature review. More generally, RNN can be used to forecast any economic variable in the sense that they do not make any prior assumptions about the variables to be predicted, since in the event of erroneous assumptions, the forecast result would be compromised.

In sum, the results of this research can be useful for public authorities in Senegal in terms of macroeconomic forecasting. They suggest two main policy implications. On the one hand, the authorities should further encourage the use of artificial neural networks for forecasting economic, monetary and financial variables. These models can capture the non-linearity in quarterly time-series data and provide forecasts that are more accurate. On the other hand, given the importance of the data required by the neural network method, the national statistical agency should be better equipped with financial and human resources to produce sub-annual data - monthly and quarterly - of all economic, monetary, financial and even social variables.

In the future, a more in-depth study using RNN models as a forecasting technique and relying on a set of variables recognized in the literature as determinants of economic growth would be interesting

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Appendices

Understanding Performance Metrics

The RMSE is written:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_t - \hat{Y}_t)^2} \tag{4}$$

This statistic measures the average magnitude of the error between the predicted value and the actual value. However, it should be noted that its quadratic character mean that it gives more weight to large error deviations. Its value ranges between [0,+∞] and the closer the measurement is to zero, the better the accuracy of the forecast.
The MAPE formula is:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t} * 100 \tag{5}$$

It calculates the average of the percentage error between the current value and the predicted values for each unit of time. It is important in the sense that it makes it possible to avoid the problems of positive and negative errors, which cancel each other out, but also penalizes less heavily than the RMSE. It is used as the loss function in this article because it is very intuitive in explaining the relative error.

The writing of the MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_t - \hat{Y}_t| \tag{6}$$

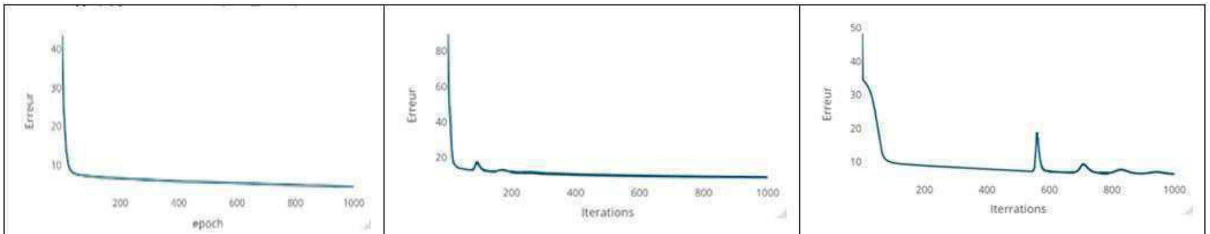
It measures the magnitude of non-directional errors in model predictions. It represents the average of the absolute differences between the predicted values and the current values. The smaller the MAE value, the higher the accuracy of the forecast model.

$$R = \frac{\sum_{i=1}^{n}(Y_{act} - \bar{Y}_{act})(Y_{pred} - \bar{Y}_{pred})}{\sqrt{\sum_{i=1}^{n}((Y_{act} - \bar{Y}_{act})^2 \sum_{i=1}^{n}(Y_{pred} - \bar{Y}_{pred})^2}} \tag{7}$$

It measures the correlation between current values and forecast values. It is defined between an interval [-1, +1]. A value close to +1 shows an almost perfect relationship between the observed data and the forecast.

Y_t represents actual values and $\hat{Y}_t$predicted values. The amplitude of the performance measures ranges between [0,+∞].

Figure 6: Convergence of model errors



One hidden layer model without re-estimation | One hidden layer model with re-estimation | Two hidden layers model without re-estimation