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Application of Machine Learning in Long Term Healthcare Cost Prediction

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Abstract

Through the years, health expenditures have been increasing among developed and developing coun-tries. Specifically, total health expenditure in Rwanda, has experienced an increasing trend, for exam- plea the total health expenditure in Rwanda was 282929; 329526 and 324385 million Rwandan francs in 2016 ; 2017 and 2018 respectively and the rise in healthcare expenditures need a rational and equity management to better provide health services efficiently and effectively. The ARIMA model has been the preferred model to forecast health expenditures for decades which later have been criticized to not capture the non-linear behavior in data. Moreover, two decades ago, the artificial neural networks (ANNs) models have got attention and improved the forecasting accuracy. However, it has been found that each of the two models has weaknesses when linear and nonlinear Behaviors are in the data, thus each of the ARIMA and ANN is no longer appropriate to model the series. Since the ARIMA model only performs better in capturing linear behavior and ANN is good in capturing non-linear behavior in data. It is with this background that, we proposed a hybrid model, which differs in combining the advantages of ARIMA and ANNs in capturing the linear and non-linear relationship in data. The ARIMA-ANNs model was tested on sets of health expenditure actual data. Our results showed the effectiveness of the hybrid model which has a higher prediction accuracy as compared to the existing models. Because of the fact, the empirical results from all of the three models considered in this study showed that from 2006 looking forward to 2027, there will be an increasing trend of health expenditure. The results showed that the forecasted values of health expenditure by ARIMA models will be 557,299.97 million Rwandan francs in 2027. While using the ANNs models, the forecasted values are 555,090.65 million Rwandan francs in 2027 and, the ARIMA-ANN models forecasted values in 2027 are 552,881.33 million Rwandan francs. This study recommends the use of the ARIMA-ANN hybrid while modeling the health expenditure.

Keywords: ARIMA; Box-Jenkins methodology; Artificial neural networks; Time series fore casting; Combined forecast

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Introduction

Worldwide, both private and public expenditures on health have been increasing through the years among developed and developing countries [1]. This raises global concerns about health and the economy, and therefore the fiscal preparations as well as policy in- terventions needed to ensure future fiscal sustainability (Centers for Medicare and Medicaid Services, 2011).

A health system is mainly composed of a couple of healthcare expenditures, which is explained as any type of spending to prevent and treat illnesses and diseases with the aim of improving the health of people. Health spending includes the three major categories of medical, hospital, and pharmaceutical expenses.

Since healthcare expenditure has been growing over years, the increase in health expenditure is explained by factors that vary according to the investigation period of time [2]. In the short-term, health spending development is mainly influenced by the health sector government budget. In the medium-term, the health ex- penditure development is influenced by the technology advancement. While in the long-run, the main factor to influence the increase in healthcare Expenditure is chronic disease prevalence. There are also other factors, such as the elderly population, economic growth, as well as the development of treatment practices [3].

Also besides, factors like population life ex- potency, population size, and population structure greatly affect healthcare spending.

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Finally, changes in consumption Behaviors have been leading to high health spending by the population. The level of personal preferences as well as the social environment through different health pro- grams such as disease prevention and health pro- motion have a magnitude impact on the level of consumption for health services and hence result in greater health expenditure.

According to the World Health Organization, 2017, the total health expenditure in Rwanda was 324,385 million Rwandan francs in 2017 where 48% of the total health expenditure was paid by the government and 52% was paid by households. Health expenditure in Rwanda is mainly financed by the public sector, and both private payment providers and insurers. In Rwanda, public employees are covered by their employers while a variety of health insurance policies is provided by private companies.

The increase in healthcare expenses has to follow the economic growth of the country (OECD, 2019), otherwise, the progressive increase in health expenditure puts a heavy burden on re- sources which in turn fails to satisfy other needs of the population. There is an essential need in controlling the health cost related policies and for a sustainable health cost policy, there is a necessity of accurate healthcare cost forecasts to avoid any sort of uncertainty. This brought a thirst to different researchers to develop different models. The main problem is that some models used in forecasting healthcare expenditure have weaknesses. A new approach is therefore needed to- forecast healthcare expenditure. The aim is to develop a more sophisticated model which is efficient in estimating the healthcare expenditure with higher accuracy than other models.

Previous studies, among others [4-6] Riemannian (2019) tried to model healthcare expenditure using ARIMA and Jo¨dicke, et al, (2019), Shahid et al (2019) have estimated the health expenditure Using ANN model.

It has been found that each of the two models has weaknesses when linear and nonlinear Behaviors are in the data, thus each of the ARIMA and ANN is no longer appropriate to model the series. Since the ARIMA model only performs better in capturing linear behavior and ANN is good in capturing non-linear behavior in data.

A closer look at the literature on the pre- diction of healthcare expenditure reveals several of gaps and shortcomings. The Rwandan context for example, Muremyi et al (2020) used the MARS model to predict out-of-pocket health expenditures in Rwanda using machine learning techniques where their findings show that the tests of the accuracy of the models were 50.16% for MARS model, 74% for decision tree model, 87% for treenet model, 83% for random forest model and gradient boosting 81%. To the best of our knowledge, there is no previous research using the ANN-ARIMA Hybrid approach to fore- cast Rwanda healthcare expenditure.

Materials and Methods

Data

The current study used the Rwanda National Health Account (NHA) data produced by the Rwanda Ministry of Health (MOH) in Partner- ship with the world health organization (WHO). The data give detailed information on Rwanda's health expenditure by both public and private sides. Note also that the data provide quarterly information from 2006 to 2018; this means that the time series data used in this study have 52 observations.

Methods

In the analysis of historical data, time series forecasting is a very famous technique for fore- casting a country's health expenditure however, healthcare expenditure data contains a mixture of linear and non-linear characteristics. There- fore, due to its complexity, a single model cannot capture all the patterns in healthcare expenditure data. As result, a variety of methods including linear and non-linear time series methods are Used in the prediction [7, 8].

Autoregressive Integrated Moving Average (ARIMA) models

ARIMA model is among the famous methods in modeling non-stationary data. The ARIMA model, rt is expressed as a function of lagged values and stochastic error components while this is not possible in linear regression models. The general and standard form of the ARIMA model is ARIMA (p, d, q). An ARIMA is presented as mentioned above, the step to follow is to carry out the diagnostic checking for the model. The importance of diagnostic inspection coefficients refer to statistical tests for residual behavior and the order of the model. If the predicted model data represents the process of emergence, the residuals behave as white-noise:

This means that the residues have not to be auto-correlated. Auto-correlation of the residue is examined by Lung-Box's Statistics Q (1978, 1979) and is defined as:

The seasonal autoregressive integrated moving average model is presented as (p, d, q) (P, D, Q), where p represents the number of auto-regressive terms, q denotes the number of moving average terms and d denotes the number of times a series must be differenced to induce stationary. And P is the number of seasonal autoregressive components Q number of seasonal moving-average terms, and D is the number of seasonal differences required for the series to be stationary (Box and Jenkins, 1994; Rockwell and Davis, 1996).

Identification: When a positive d is set to transform a no stationary series, the order (p and q) of the corresponding intermediate terms must be identified to represent the dominant features of the information. Therefore, the filtering graph procedures (ACF and PACF schemes) were used [9, 10].

Estimation: when estimating θ1, of AR and MA processes respectively, the estimation is based on the PACF and ACF, respectively. If the series is an Auto-regressive pro- cess, the coefficients are estimated by the least squares method. If there is a MA or ARMA pro- cess in this array, then non-linear estimation techniques, such as maximum likelihood, can be used to estimate parameters using numerical optimization algorithms [11].

Where, n: denotes the number of observations m: denotes the number of auto-correlation co-efficient and m = n ρs: denotes the sampled residual auto-correlation

To test whether the residuals are normally distributed, the standard residual graph along with the Shapiro-Walk test is used. When comparing the descriptive efficiency of alternative models that differ in both number of parameters and sample size, Akaike, Hannan-Quinn and Schwartz are used as the evaluation metrics. The lower the value for these three metrics, the better the model is. If partial auto-correlations and auto- correlations are both of low value, the model is then preferred as adequate for future forecasting [12].

Forecasting: The predictive method for future phase range values is derived from the previous phases, and it refers to the most appropriate model derived from the previous stages. The estimation of the Auto-Regressive Integrated Moving average model is evaluated using the Mean Squared Error (MSE) as the optimum metric. Other indicators commonly used to measure predictive accuracy are the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the Theil (U-Theil) inequality coefficient. These indicators are listed as follows

Diagnostic Checking: after the model fits

When linear and nonlinear Behaviors are in the data under study, each of the ARIMA and ANN is no longer appropriate to model the series. Thus, the models that can capture linear and non- linear patterns are preferred. Zhang (2003) stipulated Theil Inequality Coefficient is as follows:

Lasted that it is rational to develop a hybrid model that combines both ARIMA and ANN for model

(yˆt) + q(1)ΣT (y2)

Yt = Lt + Nt: Additive hybrid model

Yt = LtNt : Multiplicative hybrid model

Where, Yt represents the observation at time t

yt: denotes the actual value of the dependent

Variable y in time t,

Y t: denotes the estimated value of the dependent variable y in time t;

T: denotes the sample size.

When Theil Inequality Coefficient U=0, the estimated values are equal to the actual values of the series yt = yˆt for all t. This represents a case where the actual and predicted values perfectly fit. On the other hand, if U= 1, the forecasting is not correct for the sample being investigated [13, 14].

Artificial Neural Network (ANN) models

NNs are architecture with interconnected neurons which that aim of mimicking the functionality of the human brain [15]. The ANNs structure's main challenge is to identify the optimum number of layers and nodes in the layer in the time series pre- diction. This is determined through experiment because there is no theoretical basis for identifying the parameters. Simple architecture for ANN model of p ∗ q ∗ 1 is and Lt , Nt represent linear and non-linear parts

respectively at time t. Auto-regression is appropriate for linear component and the forecasted value is Lt at time t and Qt = yt + (Lˆ) is the residual at time [16].

Zhang (2003) confirmed that, ANN is appropriate in modelling the residuals from ARIMA which only have non-linear relationship. Using ρ input nodes, the ANN for residuals is represented as follow:

Results

The analysis focused mainly on developing a model that can accurately predict the total health

Here, j (j0, 1, 2...q), ij(i0, 1, 2...p; j0, 1, 2...q) expenditure in Rwanda [17-20].

Data visualization and exploration

We first visualized the data using the matplotlib function through its library called "pyplot" to see if there are any trend and seasonality in data. This is crucial and is important due to the fact that to estimate using historical data, we first need to ensure that the data are stationary, therefore, data visualization is one of the preliminary steps toward checking the stationary of the time-series data (**Figure 1**).

From Figure 1, it is noticeable that there is an overall increasing trend in health expenditure data along with some seasonal variations. How- ever, it is hard to confirm the trend from the graph, for further confirmation of the stationarity, we check the following statistics:

Rolling Statistics: by plotting the moving average and see if it varies with time. By moving average/variance, this means that at any instant's', the average/variance of the last year is considered. But again, this is more of a visual technique. In addition to this, ADF which is the famous test for stationarity testing is used. The null hypothesis that states that the data has a unity root are rejected when the p-value is less than 0.05. Even if the variation in standard deviation is small, the mean is continuously increasing with time indicating that the series is not stationary. Also, looking at the test statistic is larger than the critical values since the p-value of 0.980194 is higher than 0.05, this means that health expenditure data is not stationary. Next, we'll apply different techniques to take the time series towards stationery [21].

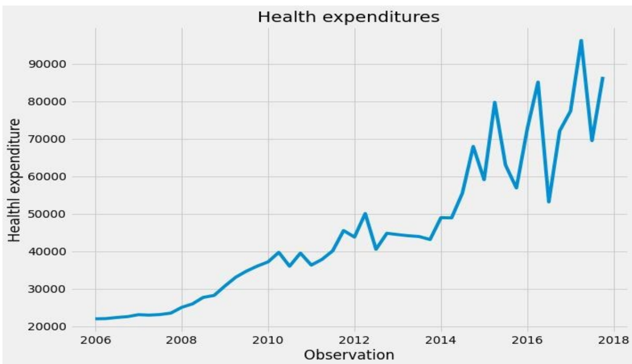

Figure 1 Health expenditure data visualization.

Model estimation and removing trend

For historical data to become stationary, the first step is to remove the trend and seasonality from the data. We used the transformation techniques to normalize the data and remove the rising trend. After the logarithmic transformation, the rolling statistic was computed. A rolling average was computed from taking input for the past 12 months and assigning a mean expenditure value at every point further ahead in the series (**Figure 2**), (**Table 1**).

The results from the transformation showed that the series has no longer a unit root. How- ever, in some cases, the seasonality appears high in the data. In such situations, eliminating the trend does not help much. Instead, more attention is on the seasonality in data. Differencing is the famous method for this task.

Differencing is used to eliminate the series dependence on time which includes trends and seasonality. Differencing helps in stabilizing series by eliminating the variation in the level of a series, reducing the magnitude of both seasonality and trend. Differencing is conducted by taking the difference between previous and present values [22].

Finding the best parameters for model

Before building the forecasting models, we first identified the optimal parameters for the forecast- ing models. We plot the ACF and PACF and a non-seasonal ARIMA model stated in the form of ARIMA (p,d,q) (**Figure 3**).

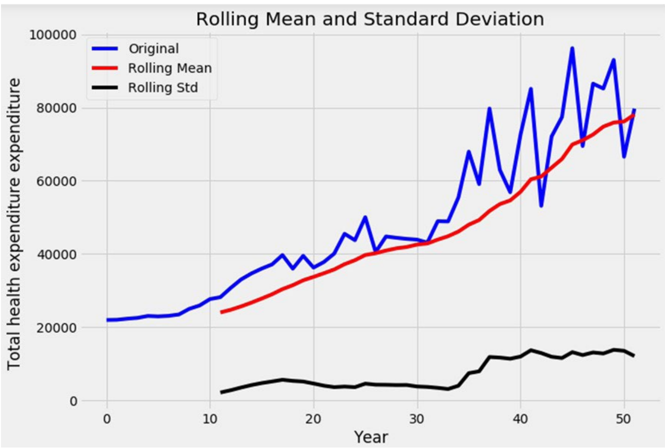

Figure 2 Rolling statistics for total health expenditure.

Table 1. Dickey-fuller test for total health expenditure.

Result of Dickey fuller test	
Test statistics	0.366406
P-value	0.980194
No. of lags used	7.000000
Number of observations used	44.000000
Critical value (1%)	-3.58857
Critical value (5%)	-2.92989
Critical value (10%)	-0.60319
dtype: float64	

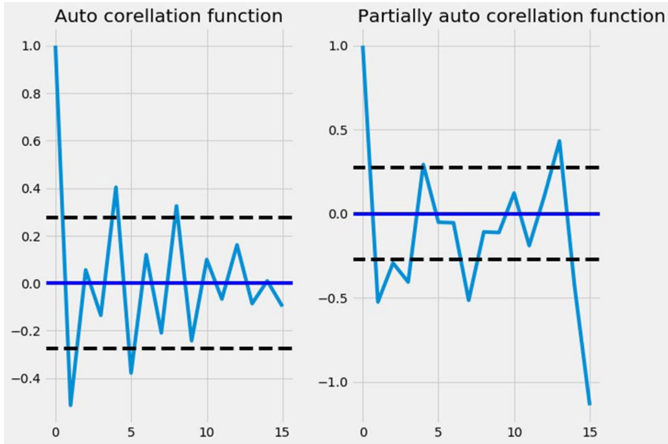

Figure 3 ACF and PACF for total health expenditure.

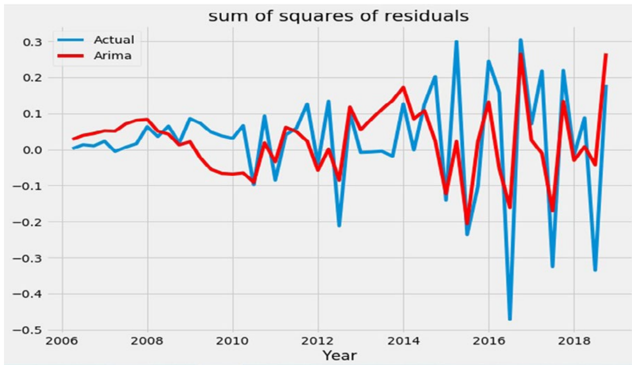

Figure 4 ARIMA (1,1,1) model fit for total health expenditure.

Fitting model

To identify the best parameters, we first check, where ACF and PACF graph for the first time

Breaks off the root or decreases to zero. Looking at Figure 3, p and q values are close to 1. The ARIMA (1,1,1) is the tentative ARIMA model for health expenditure (**Figure 4**).

Looking at Figure 4, which maps the actual and ARIMA (1,1,1) estimates, we noticed the small deviation of estimated values from actual values showing that the model fit is good. The results in the table below show that, the AR (1) coefficient is significant since its p-value of 0.004 is less than 0.05. However, the coefficient of MA (1) is not significant Considering also the standard errors of coefficients, the standard error of AR(1) coefficient is 0.214 and the standard error for MA(1) coefficient is 0.283 (**Table 2**).

Predictions

The ARIMA (1,1,1) predictions as indicated by Figure 5, show that the total health expenditure in Rwanda will continue to increase in the long running the model (**Figure 5**).

Artificial neural-network and hybrid model

After the model training, we evaluated the performance of the

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Table 2. ARIMA model results.

Dep.Variable	D.y	No. Observation	33			
Model	ARIMA (1,1,1)	Log Likelihood	-303.183			
Method	css-mle	S.D. of innovations	2351.405			
Date	Fri,22 May 2020	AIC	614.365			
Time	14:32:30	BIC	620.351			
Sample	04-01-2006	HQIC	616.38			
	-2019					
	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	837.9728	292.533	2.865	0.008	264.618	1411.328
ar.L1.D.y	-0.6749	0.214	-3.16	0.004	-1.094	-0.256
ma.L1.D.y	0.1877	0.283	0.662	0.513	-0.368	0.743
	Real	**Imaginary**		**Modules**		**Frequency**
AR.1	-1.4817	0		1.4817		0.5
MA.1	-5.3262	0		5.3262		0.5

Table 3. Forecast for total health expenditure data.

Measures of fit (Training set)	Forecast accuracy (Testing set)							
	MD	SD	MAD	MSE	MAPE	MAD	MSE	MAPE (%)
ARIMA	0.3023	0.35634	0.1149	0.0102	3.6023	0.1115	0.0159	3.713
ANN	0.3198	0.4189	0.1178	0.0104	3.5042	0.11	0.0168	3.498
Hybrid	0.309	0.3679	0.1029	0.0062	3.3438	0.0099	0.0075	3.543

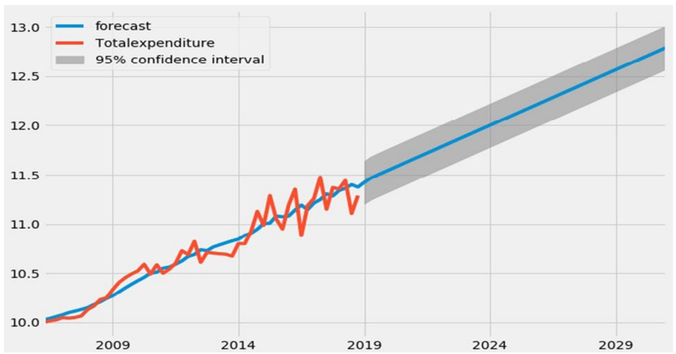

Figure 5 Ten years forecast for total health expenditure.

model on both the training data and on test data In this analysis, we split the series into train and test data sets with 60% of the observations being for training and the remaining 40% for testing the model.

Empirical results from fitting all three models

After fitting the models the performance was evaluated using three performance metrics namely MAD (Mean Absolute Deviation), MSE (Mean Squared Error), and MAPE (Mean Absolute Percentage Error) (**Table 3**).

The results presented in Table 4 shows that the same ANN architecture of 18 X 9 X 1 provided accurate predictions than both the ARIMA and ANN models. The ANN-ARIMA Hybrid model provided accurate forecasts than other models. In relation to MAD, MSE and MAPE, the ANN- ARIMA Hybrid model improved the predictive.

Capability compared to the remaining models. Figure 6 shows the forecasted and actual values produced by the three different models. We noticed that the predicted values for the ARIMA-ANN model are closer to the actual values than the two remaining models.

All models employed in the analysis showed those ten years ahead, there will be an increase in total healthcare expenses. The forecasted values by ARIMA models will be 557,299.97 million Rwandan francs in 2027 quarter-four from 87,270.89 in 2017 quarter four. While using the ANNs models the forecasted values are 555,090.65 million Rwandan francs in 2027 quarter-four from 86,924.92 million Rwandan francs in 2017 quarter four. And ARIMA-ANN models forecasted values in 2027 are 552,881.33 in million Rwandan while they were 86,578.95 million Rwandan francs in 2017 quarter four.

Discussions

It is worth discussing these interesting facts revealed by the results from both traditional and machine learning-based approaches to analyze, forecast, explain, and present the time series data of health expenditure in Rwanda. Comparing with other models, the best model has been selected as the final model. We provided also a method for prediction and forecasting based on data, which is applicable and useful to governments and insurance companies.

First, we used the Box-Jenkins procedure to model Total, government and household health expenditure in Rwanda. The time series was found to be non-stationary in mean and variance. Transformation and differencing suitably rendered the series stationary. The analysis on healthcare expenditure time series in Rwanda and the established model showed that the ARIMA model by the B-J method has good forecasting validity when modeling analysis is made for non- stationary time series.

The results in this thesis showed the superiority of the models

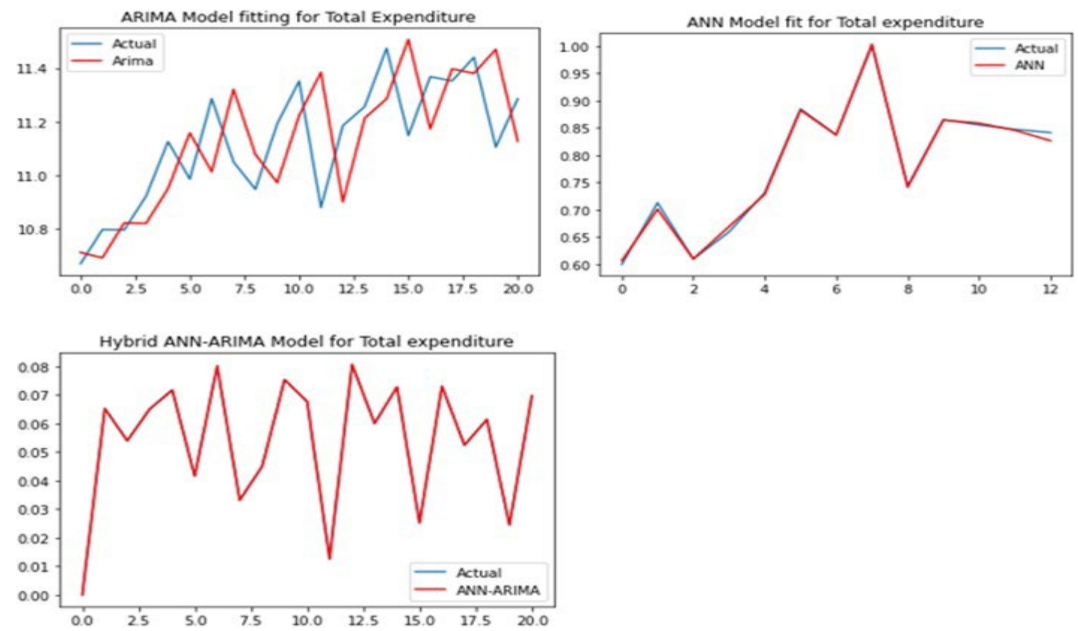

Figure 6 Actual and predicted values for health expenditure.

established by using the radial ba- sis functions than other methods. Consequently, the results showed that the ANN-ARIMA Hybrid out-performed the ARIMA and neural network models. The forecasting error for the ARIMA models is slightly higher than the forecasting errors for both neural network ANN-ARIMA hybrid approaches. This tells how weak the ARIMA models are when compared to neural network and ANN-ARIMA approaches. Therefore, the use of neural networks and ANN-ARIMA hybrid-based models to predict healthcare expenditure is pre-Overall; the Hybrid model is the one that obtained the most robust results with higher ac- curacy than other proposed models.

The results of this thesis agree with the work of (Wang, et al, 2013) that compared the traditional models like ARIMA with ANNs architecture and they concluded their study saying that the ANNs models showed the superiority in forecasting over the traditional models (**Figure 6**).

Note also that, the predictive capability of the ANN model is higher than the ARIMA model in terms of predictive capability from the test data. Figure 4 shows that both ANN-ARIMA and ANN models perform better when compared to ARIMA models for healthcare expenditure forecasting. We noticed that the ARIMA model has a directional pattern, as shown in Figures 1 and 2 while both Hybrid and ANN models are to- ward the value prediction. This work also agrees with the results of (Zhang, 2012) that the hybrid approach performs better than ARIMA and ANNs models when applied separately. Hence, this research work also confirms the opinions re- ported in the literature that the ANN-based models are superior in predictive capability over the ARIMA model in time series forecasting.

Concluding Remarks

This study compared the predictive capabilities of three models namely ARIMA, ANN and ARIMA- ANN to predict total health expenditure. The results showed the effectiveness of the hybrid model which has higher prediction accuracy as compared to other models considered in this study.

At last, the ten years forecasts showed that health expenditure and household expenditure will experience an increasing trend in the long run.

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