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Machine Learning for Economic Modeling:
An Application to South Africa's Public Expenditures

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ABSTRACT

Accurate estimate of public expenditures is needed for budgetary planning and government decision making. Recent advances in machine learning offer the opportunity for modeling such problems. The paper introduces a novel modeling approach using a machine learning tool to forecast public expenditures and compares and contrasts the effectiveness of this approach to traditional modeling alternatives. This research uses historical quarterly data from 1960-2016 to model public expenditures. Various accuracy measures (MAD, MAPE, and RSME) show that the machine learning model is the best alternative formulation and offers 97% forecasting accuracy. This model allows government decision makers to assess alternative policies with specific budgetary impacts. Furthermore, the study also shows that population aging is an important predictor of public expenditures, suggesting that demographic monitoring is indispensable for efficient fiscal planning and management in South Africa.

KEYWORDS

ANN, ARIMAX, Budgetary Forecast, DAN2, Government Expenditure, Machine Learning

INTRODUCTION

The South African public policy budget continues to rise with a spending growth of about 49% over the last decade; moving from ZAR 33764 billion ($2597 billion) in 2010/2011 to ZAR 1.79 trillion ($0.16 trillion) in 2018/2019. Included in this expenditure category are health care and social protection, which represent respectively 12% and 14% of the total government spending in 2018 (SSA, 2015 and 2019) and are expected to escalate with aging population. South African population is estimated at 57.3 million in 2018, 8.3% of whom are aged over 60 years, with a predicted increased in the share of elderly to 9.1% in 2022. While the old age grant has grown to about 30% of the social spending in 2019, the country faces a hiking chronic disease burden as more South Africans live beyond the age of 60 years (Solanki et al., 2019). In addition to the Covid-19 outbreak, which has triggered the health spending, 40% of older population in South Africa are poor and depend entirely on the government for their basic survival. The uncertainty about the future increase requires accurate forecasting of such expenditures, in order to assist government policy makers with their planning, assessment, and budget allocation in support of funding decisions. The present study addresses this specific objective by introducing a machine learning model to forecast public expenditures based on

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the historical trend in population aging; with the ultimate goal of providing a new support framework for the budgetary policy decision.

A sound governmental fiscal planning and management requires accurate expenditures predictions. This is particularly crucial for developing countries characterized by persistent budget imbalances. In addition, modifications in fiscal expenditures due to unanticipated changes in socio-economic and demographic conditions entail delayed effects, which necessitate accurate forward-looking policy strategies and/or actions. To address such uncertainties, the economic and forecasting literature (Lassila et al., 2014; Kudrna et al., 2015) advocates incorporation of both demographic and macroeconomic factors in predicting future government expenditures.

Existing literature offers a variety of approaches for forecasting government expenditures using time series-based forecasting. Recently, researchers have proposed Artificial Neural Networks (ANN) as an alternative approach to time series-based forecasting (Zang et al., 1998; Zang, 2003; Ghiassi et al., 2006; Ghiassi et al., 2008; Ramyar & Kianfar, 2019 among others). For example, Ghiassi et al. (2006) introduce a dynamic architecture for artificial neural network (DAN2) to forecast electric consumption for Taiwan, and Ghiassi et al. (2008) follow the same methodology to forecast urban water demand for the city of San Jose, California. They find that DAN2 delivers exceptional fit and forecasts using time series datasets. Similarly, Basaran et al. (2010) implement a feed forward neural network architecture to forecast public expenditures in Turkey and obtain high prediction precision. In the same vein, Ramyar & Kianfar (2019) compare the forecast ability of a multilayer perceptron neural network to the vector autoregressive model in forecasting oil prices and conclude that machine learning improves prediction accuracy.

This study aims to develop a model based on a traditional approach (ARIMAX) and compare and contrast its performance against a model based on DAN2 to predict government expenditures in South Africa. The accurate forecast values from these models can be used to assist policy makers to better manage and/or keep fiscal imbalances at sustainable levels. Moreover, with the increasing pace of elderly cohort expected to trigger fiscal pressures, this study addresses the inclusion of demographic changes and analyses the role of population aging in such forecast models.

In fact, in most developing countries, government is the primary funding support for old people whose vulnerability has been triggered by poverty and inequalities. In addition to offering free health care, the aged population group in South Africa is also entitled to the financial assistance in the form of social grant (old age grant) with a significant eligibility increase since the political transition in 1994[1]. Consequently, public expenditures on pension in South Africa are expected to rise by 3.3% in 2050 from 2.2% between 2003 and 2015 (OECD, 2019). The improvement of the health system in South Africa has also increased life expectancy while the retirement age has not been increased proportionally. Since the existing government revenue cannot keep up with demand, policy decisions including "qualification age" must be considered and any such decision to "rationing of funds" will require accurate expenditures forecasts.

While fiscal policy and its macroeconomic impact have been studied in South Africa (Akanbi, 2013), it is surprising how public expenditures forecasting has received very little or virtually no attention. With the increasing pressure on government expenditures due to rapid changes in socio-economic and demographic structures, informed decision has become an imperative to achieve efficient budget allocation. In effect, public expenditures forecasting forms part of the modern methods of public finance management. While such a forecast involves the inclusion of a wide range of variables, artificial neural networks provide an edge over traditional forecasting approaches owing to its potential to capture complex relationships. Thus, this paper offers a base for the analysis of the potential budgetary implications of the government social policy in South Africa.

The rest of the paper is organized as follows. Section 2 succinctly reviews the literature on expenditures modelling in relation to the fiscal environment. The methodology and empirical analysis are presented in sections 3 and 4, respectively. Section 5 presents the policy recommendations and the concluding remarks are discussed in section 6.

LITERATURE REVIEW

In the fiscal literature, government expenditures forecasting has evolved across time mainly due to the development of improved forecasting methods. From the regression analysis to the time series approaches, many studies predict that economic, social, demographic, institutional and political variables help explain the trend in public expenditures. Borcherding (1985) surveys the causes of government expenditures growth in the US and finds that familiar substitution, income, population/ public good-tax sharing effects contribute to about 40% of the government spending besides institutional factors including rent-seeking, political redistribution, and bureaucracy. Peacock (2004) emphasizes that economic growth is a key driver of public expenditures in selected industrialised countries while Dizaji (2014) shows that oil price is an important predictor of public expenditures in oil exporting countries. In developing countries, the degree of openness, the level of economic development, the rent-seeking behaviour and the demographic factors are emphasized in explaining the growth in government spending (Fan et al., 2008). While higher proportion of young cohort affect the demand for education spending, population aging resulting from the demographic shift induces higher spending demand of health care, housing and social security (Murthy & Okunade, 2016; Braendle & Colombier, 2016, Jimeno et al., 2006).

While the number and/or quality of predictor matters for the forecasting accuracy, the prediction precision is also driven by the forecasting method employed. Some researchers, Timmermann (2006) have offered grouping of the forecast methods (combinations or ensembles) in order to provide a more accurate forecasts over the best single model; the principal attraction being the possibility to hedge against model uncertainty. They postulate that forecast combinations, make use of various information sets, predictors, and modeling structures to better accommodate structural break than single model while alleviating the potential misspecification bias and measurement errors (Ghysels & Ozkan, 2015).

The most recently used class of forecast combinations is the mixed data sampling (MIDAS) models which consist of pooling different specifications to compare the forecasting performances of different predictors (Kuzin et al. (2013). An illustrative example is Andreou et al. (2013) who combine many cross-sectional financial series to derive MIDAS predictors of output growth. Marcellino & Schumacher (2010) use the factor-MISDAS models based on the parsimonious principal component analysis whereas Andeou et al. (2011) build a MIDAS with autoregressive distributed lag (ADL-MISDAS) models to accommodate mixed frequencies indicators (daily and quarterly). ADL-MISDAS models have also been applied by Ghysels & Ozkan (2015) to forecast US federal government budget using root mean squared forecast errors (RMSE) as accuracy metric. Their combination includes fiscal and macroeconomic indicators at different frequencies.

Despite the wide range of predictors, government expenditure forecast has generally been characterised by inadequate accuracy; possibly due to the forecasting technique used. Though the omission bias might be an important source of poor accuracy, Vasconcelos de Deus et al. (2017) explore various dimensions of government budget balance forecast in Brazil including, economic, political, intuitional, and find that the forecast is indeed of low quality and inefficient. They conclude that forecast errors are due to backward-looking effects and cyclical fluctuations. Similarly, Ericsson (2017) detects biases in the US government forecast of the federal debts and argues that these biases are closely linked to turning points in the business cycle. This suggests the inability of the existing techniques to better capture the nonlinearity induced by the cyclical movement in both predictors and predicted variables.

The time series forecasting toolbox comprises several approaches categorised into linear, nonlinear and hybrid. The linear forecasting literature is dominated by the popular autoregressive integrated moving average (ARIMA), applicable in both univariate and multivariate frameworks, which has found worthwhile applications in many disciplines such as social, financial, economic, environmental and engineering. Given the restriction to linear problems, ARIMA was further extended to nonlinear frameworks which led the development of parametric nonlinear methods such as threshold autoregressive (TAR), autoregressive conditional heteroscedastic (ARCH) and general autoregressive conditional heteroscedastic (GARCH) among others.

However, due to misspecification bias and over-parametrisation (particularly severe in multivariate contexts) attributed to parametric nonlinear forecasting models (Khashei & Bijari, 2011), non-parametric approaches such as ANN, have recently received increased attention in time series forecasting. ANN methods offer the following advantages. (i) flexibility in nonlinear mapping enabling the approximation of any continuous function; (ii) imposition of a few restrictions to the data generation process of the observed time series which reduces the misspecification bias; (iii) potential to adapt and remain robust and accurate in nonstationary environment subject to changes across time; (iv) computational benefit by using less parameters than the alternative polynomial, spline and trigonometric expansions with similar approximation rate (Khashier & Bijari, 2011).

The overwhelming attraction to ANN has further materialised in empirical studies which confirms the evidence of accurate forecasting from ANN approaches (see for example Chakraborty et al., 1992; Poli & Jones, 1994; Cottrell et al., 1995; Balkin & Ord, 2000; Berardi & Zhang, 2003; Chen et al., 2005; Jain & Kumar, 2007; Giordano et al., 2007 among others). Although the comparative analysis between ANN and traditional forecasting methods, either linear or nonlinear, at time may provide mixed results (Foster et al., 1992; Taskaya & Casey, 2005), it seems that ANN may perform as good as linear alternative under ideal conditions or when using relatively high frequency data (Tang, 1991; Tang et al., 1993; Zang et al., 1998). According to Denton (1995), ANN outperform the linear models in the presence of misspecification, multicollinearity and outliers; suggesting that ANN solution is appropriate for complex dynamic systems.

Though Ghysels & Ozkan (2015) document the ability of real time forecasting models with mixed frequency data in improving government budget forecast, this multivariate framework is data-driven and therefore might not be appropriate for developing and emerging contexts due to lack of available data. Moreover, public expenditures are subject to multifaceted dynamics (economic, demographic, social, environmental, political…) which render its prediction a difficult task. However, ANN methods have recently emerged as the decision support toolbox given their ability to deliver excellent performance when complex relations exist between variables. Basaran et al. (2010) report a relatively high prediction precision of public expenditures in Turkey using the feed forward, back propagation (FFBP) architecture. Likewise, Jang (2019) demonstrates the effectiveness of machine learning models in boosting the efficiency of the budget allocation plan using the Korean R&D program. He shows that simulated budget allocation plan using machine learning can deliver an output up to 13.6% higher than the actual R&D output. This conclusion is consistent with Nikolopoulos et al. (2021) who confirm the performance of machine and deep-learning models for planning and forecasting government decision such as lockdown. While various algorithms exist, the unanimous inference that machine- and deep-learning models are effective decision support systems might possibly point to their convergence. Unlike the static framework, this study exploits the dynamic Architecture for Artificial Neural Network (DAN2) which provides more flexibility and a larger spectrum of nonlinear approximations with the expectation of better accuracy (Ghiassi et al., 2006).

Furthermore, because the data generation process of a time series is likely to comprise both linear and nonlinear components, component models for forecasting also known as hybrid forecasting techniques, have been recently recognised as the optimal solution for accuracy improvement; hence shifting the attention to hybrid ANN. Khashier & Bijari (2011) provide the evidence that hybrid ARIMA- ANN models overcome the inconsistency related to ANN forecast in comparison to traditional time series models. In line with the hybrid approach and considering that cyclical variabilities are often cited as a major source of error forecast of public expenditures (Ericsson, 2017 and Vasconcelos de Deus et al., 2017), this study proposes DAN2 as a promising solution to public expenditures forecast. To the best of authors' knowledge, this is the first such attempt for public expenditures forecasting in South Africa. In addition, the empirical strategy accounts for exogenous changes in population structures, which represent an important driver of public expenditures growth in developing countries and particularly in South Africa (Perey, 2016; Solanki et al., 2019). The paper therefore offers two forecasting models for the analysis: ARIMAX and DAN2.

3. METHODOLOGY

Though it is rational to expect government expenditures to be influenced by economic fundamentals, internal forces such as fiscal goals, policies and strategies are likely to also play an important role. Moreover, as indicated earlier, social security goal has been one of the key development strategies in South Africa, particularly in the post-apartheid administration. Not surprisingly, social benefits form an important component of the total expenditures. And given the subjection of this expenditure's category to demographic development, government spending is also expected to be impacted by demographic factors. Therefore, government expenditures are not only influenced by its own passed declared values but also by other exogenous predictors, namely economic and demographic. For modeling purposes, this can be reduced to presentation of government spending as a time series process based on GDP and demographics values, that is, public expenditures to GDP ratio as a time series function and one exogenous predictor: demographics.

ARIMAX Models

The traditional modeling solutions use multiple regression models in which the total public expenditures are set to be explained by a set of predictors such as economic, financial, social, political and demographic variables (Borcherding, 1985; Fan et al., 2008). Following Box and Jenkins (1976), the ARIMA modeling approach has become a standard forecasting tool. ARIMA is based upon a simple principle that the history of a time series represents the information set required to efficiently predict its future behavior. Box-Jenkins specification can be viewed as a multiple regression model with a single independent variable (*x*), and at least one autoregressive (AR) and/or moving average (MA) terms. Accordingly, let y_t be the expenditures variable, the structure of ARIMA (*p, d, q*) is given by the following equation:

$$y_t = \alpha + \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + ... + \gamma_p y_{t-p} + e_t - \phi_1 e_{t-1} - \phi_2 e_{t-2} - ... \phi_q e_{t-q} \tag{1}$$

where p and q are the lag length of the AR and MA components, respectively and d is the order of integration; y_{t-i} ; $i = 1,..., p$ are the AR terms and e_{t-j} ; $j = 1,..., q$ are the MA terms.

Formulating this problem as an ARIMAX, the structure of ARMA (*p, q*) derives from the general ARMAX (*p, q*) model in which there are p autoregressive and q moving average components, respectively.

$$y_t = \alpha + \beta x_t + \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + ... + \gamma_p y_{t-p} + e_t - \varphi_1 e_{t-1} - \varphi_2 e_{t-2} - ... - \varphi_q e_{t-q} \tag{2}$$

ARIMAX *(p, d, q)* has a structure which is similar to ARIMA (*p, d, q*) where the time series is differenced d^{th} ; the differencing transformation helps to achieve stationarity for non-stationary variables. This specification emphasizes the importance of exogenous changes in improving the prediction performance.

Because this model imposes the normality assumption and models only linear relationships, a more realistic modeling framework is considered, capable of capturing more complex relations including nonlinear associations. Machine learning tools offer a learning engine that can be based on a variety of formulations. Popular approaches have used linear regression, Bayesian approach, decision trees, genetic algorithms, artificial neural network (ANN), and more. Overall, machine learning tolls are data driven and use a "training phase" to learn the behavior of the underlying processes. As such these models use "computational statistics" to capture a model and to forecast future behavior. The trained models are always calibrated with "out-of-sample" datasets to avoid model under/over fitting. The machine learning tools, including ANN based systems, are shown to be a very effective modeling tool for solving complex, nonlinear, time series problems. The traditional ANN models are based on FFBP algorithm and are extensively suited in the literature (Zang et al., 1998; Zang, 2003; Tang & Fishwich, 1993; Basaran et al., 2010). Recent advances in ANN have introduced more effective architectures. One such model, DAN2, was introduced by Ghiassi & Saidane (2005) and is shown to be very effective for various modeling problems, including time series events (Ghiassi et al., 2006; Ghiassi et al., 2008; Wang et al., 2010). The prediction accuracy of DAN2 is reported to be better than the traditional ANN, ARIMA or various other modeling approaches (Ghiassi et al., 2006; Ghiassi et al., 2008; Wang et al., 2010; Velasquez & Franco, 2010; Guresen et al., 2011, amongst others). This motivates the use of DAN2 in this research, which is briefly summarized in the next section.

A Dynamic Architecture for Artificial Neural Networks

Forecasting government expenditures is a complex process with often multiple variables forming a nonlinear and/or a linear relationship. Machine learning tools can offer an effective alternative solution for forecasting such processes. Machine learning tools use a variety of linear and nonlinear estimation engines to capture the underlying pattern and behavior of processes. Among the various machine learning engines, ANN-based systems are shown to be more effective than other alternatives solutions (Zang et al., 1998; Zang, 2003; Ghiassi et al., 2006). The study offers a neural network-based machine learning solution for forecasting government expenditures for South Africa that produces highly accurate results. More specifically, use is made of the Dynamic Architecture for Artificial Neural Network (DAN2), introduced by Ghiassi & Saidane (2005), in this research. As stated in section 2, researchers have shown DAN2 as a promising solution to public expenditures forecasting. We briefly present basic concepts of this approach and how it differs from traditional ANN and refer readers to Ghiassi & Saidane (2005) for detailed theoretical description of DAN2 as well as its application to a host of problems in various domains.

The traditional ANN models have been extensively studied in the literature with numerous applications (Zang et al., 1998; Ghiassi et al., 2006; Ghiassi et al., 2008; Ramyar & Kianfar, 2019 among others). ANN models are multilayer feed forward, back propagation (FFBP) based. The FFBP neural network architecture is comprised of an input layer, one or more hidden layers, and an output layer. The choice of architecture is problem dependent and often requires experimentations before a final architecture is selected for training and ultimately forecasting. These models are many-to-many networks and become complex as the number of variables, hidden layers, and/or number of hidden nodes increases. Estimation of the many parameters associated with such a model is one reason that most analysts limit the number of layers to a few (often 2 or 3 layers) and the number of hidden nodes per layer to few nodes as well. These restrictions can reduce model accuracy. Yet still, for complex problems, especially those with underlying nonlinearity and/or time series formulation, ANN solutions have produced better results that alternative approaches (Zang et al., 1998; Ghiassi et al., 2006).

DAN2 is a neural network-based architecture, that similar to ANN architecture, uses an input layer, hidden layers, and an output layer. However, DAN2 differs from traditional ANN in many respects. First, DAN2 is a feed forward, dynamic neural network in which hidden layers are dynamically, sequentially, and automatically created until a desired level of accuracies is reached. The model uses the entire transformed input data at every iteration to learn and accumulates knowledge at each layer, propagating and adjusting this knowledge forward to the next layer, and repeating these steps until the desired network accuracy is reached. The overall architecture is presented in Figure 1. Internally, DAN2 ensures that over/under fitting is avoided even if the stated accuracy level is untenable thus requiring revision and restatement of a new accuracy level. Therefore, analysts, using DAN2, do not need to experiment with various network architectures, but instead, DAN2 automatically generates the best architecture for the problem.

Another distinction of DAN2 is the transfer function used in the architecture. Traditional ANN architectures use sigmoid function to capture the nonlinearity of the process. DAN2 uses Fourier Transfer instead. Fourier transfer are shown to be an excellent alternative for function approximation (Bloomfield, 1976). DAN2 uses this transformation at the input data level to project every record onto a reference vector R = { r_j ; j = 1, 2, . . ., m}, to normalize input data. Vector R is an m-dimensional vector where m represents the number of attributes in data records. At every iteration, the normalization introduces a new angle, α_k , between records and the reference vector. DAN2 at each layer modifies the reference vector, by moving and rotating it, thus revising α_k , and measures the contribution of each record to the output of the learning process. The collective contributions of this process can be represented by four components as described by Eq. (3)

$$F_k\left(X_i\right) = a_k + b_k F_{k-1}\left(X_i\right) + c_k G_k\left(X_i\right) + d_k H_k\left(X_i\right) \tag{3}$$

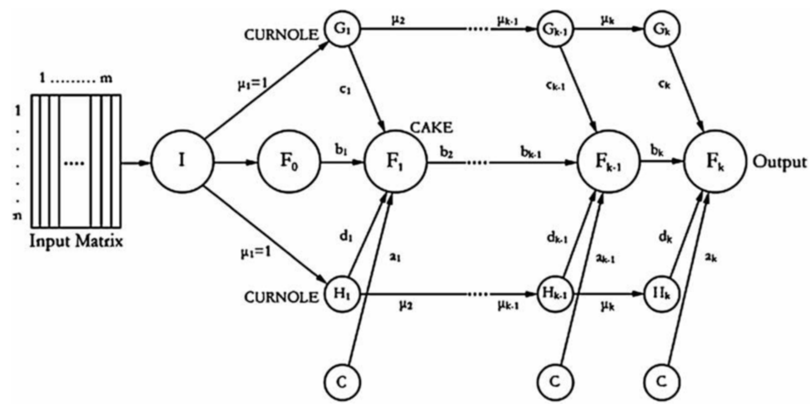
where X_i represents the n independent input records, $F_k\left(X_i\right)$ represents the output value at layer k, $G_k\left(X_i\right)$ = Cosine ($\mu_k \alpha_i$), and $H_k\left(X_i\right)$ = Sine ($\mu_k \alpha_i$) represent the transferred nonlinear components, and a_k, b_k, c_k, d_k and μ_k are parameter values at iteration k. The four elements on the right-hand side of Eq. (3) correspond to the four nodes (C, G_k, , H_k, , and F_{k-1}) in Fig.1. At each layer, DAN2 uses the previous four nodes as the input to produce the next output level. Therefore, DAN2 is a many-to-one architecture and is less complex than the many-to-many configuration of the FFBP models.

DAN2 training process initially captures the linear component of the process by using OLS or other simple methods to compute a starting point. If the desired level of accuracy is reached, the training terminates. Otherwise, the model generates additional layers to capture the nonlinear component of the process by minimizing a measure of total error (such as SSE or RMSE) as represented by $SSE_k = \sum\left[F_k(X_i) - \hat{F}_k(X_i)\right]^2$. Substituting $F_k(X_i)$ from Eq. (3) results in:

$$SSE_k = \sum\left[a_k + b_k F_{k-1}\left(X_i\right) + c_k \operatorname{Cos}(\mu_k \alpha_i) + d_k \operatorname{Sin}(\mu_k \alpha_i) - \hat{F}_k(X_i)\right]^2 \tag{4}$$

where $\hat{F}_k(X_i)$ are the observed output values. Minimizing Eq. (4) requires the estimation of five parameters. This formulation is linear in the parameter set A_k , where $A_k = \left\{a_k, b_k, c_k, d_k\right\}$ and nonlinear in parameter μ_k . Parameter set A_k are easily estimated using OLS. In Ghiassi and Saidane (2005), they present several nonlinear optimization strategies to estimate the nonlinear parameter μ_k . They also show that following this approach, at each layer the knowledge gained is monotonically increased, total error is reduced, and the network training improves. This property of DAN2 introduces knowledge memorization to the model. In Ghiassi et al. (2005), the authors compare DAN2 with traditional FFBP and recurrent neural network (RNN) models. The comparison spans both theoretical and computational perspectives using several benchmark datasets from the literature. Performance of DAN2 against these models as well as non-neural network alternatives is also presented. Their studies show that DAN2 outperforms all other alternatives and produces more accurate training and testing results in every case. Additionally, the authors in Ghiassi et al. (2005) use DAN2 with a host of time series problem and compare its performance against alternative solution strategies. Their results show DAN2 to be more accurate and performs significantly better than the traditional neural network and autoregressive integrated moving average (ARIMA) models.

Figure 1. DAN2 architecture (see Ghiassi and Saidane (2005))



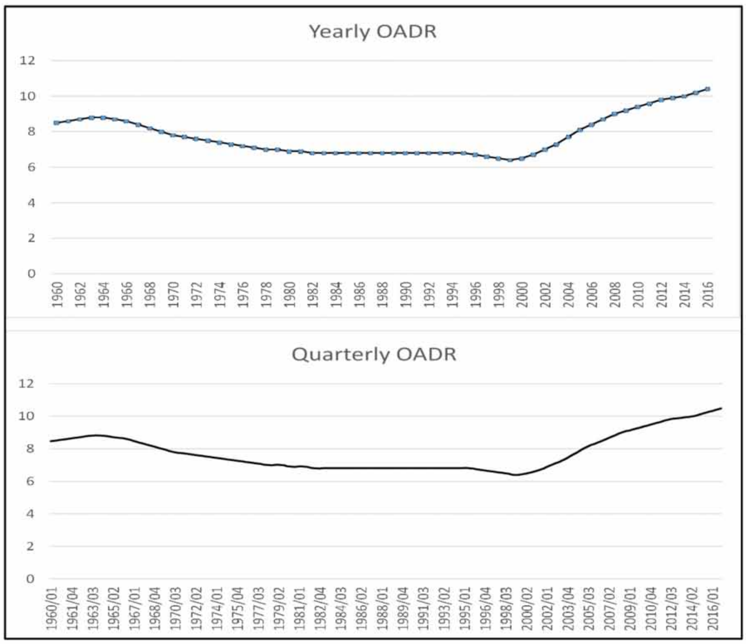
In the forecasting literature, the Root Mean Squared Error (RMSE) has commonly been used to assess the forecast accuracy; the smaller the RMSE the better the accuracy. Accordingly, the recent forecast of the US government budget by Ghysels and Ozkan (2015) reports for the 1-step to 4-step ahead forecast horizon, RMSEs ranging from 2.601 to 2.733 with the naïve model (AR); 2.386 to 2.640 with the Augmented distributed Lag (ADL) and 1.648 to 2.311 with the MIDAS. Some machine learning algorithm use some performance criteria (such as RMSE) as a stopping criterion. The empirical analysis uses this guideline to assist us in reaching a low RMSE value, such as the RSME value of 1.648 obtained by Ghysels & Ozkan (2015) from the MIDAS models, in the forecasting models. As noted in Ghiassi & Saidane (2005), defining a minimum value for RMSE as a stopping rule may not always be attainable, in such cases, the study reports the lowest RMSE obtained for each model. DAN2 is employed in this research, and we compare its performance with ARIMAX to show its effectiveness for forecasting government expenditures for South Africa.

EMPIRICAL ANALYSIS

Data and Preliminary Analysis

The empirical investigation makes use of quarterly data for South Africa from 1960 to 2016. Included in the analysis are: expenditures as a percentage of GDP (EXP/GDP) and old age dependency ratio defined as the ratio of old population to the working age population-(OADR). The data for these variables is obtained from the Federal Reserve of Saint Louis (FRED) Database, however, unlike the expenditures ratio of GDP, the aging variable is available at the annual frequency only. The study transforms the annual data into quarterly figures using quadratic polynomial interpolation. In this data conversion method, local quadratic polynomial fitted values of each low frequency series are used to replace all observations of the high frequency series at the corresponding time period. The polynomial transformation is achieved by collecting groups of three contiguous points from the initial series and fitting a quadratic function such that either the mean or the total of high frequency points matches the observed low frequency source series. In general, the three points are obtained by choosing one point before and one point after the time being interpolated. However, for end points, both time periods are drawn from the side where the data are available[2]. Figure 2 depicts both transformed and untransformed series which display similar trending behavior. Finally, it is ensured that for each year the sum of the quarterly values match the corresponding actual yearly value.

Figure 2. Aging trends



The preliminary analysis in Table 1 (Panel A) displays a small probability of the Jarque-Bera test of normality for the demographic variable (OADR); indicating a rejection of the null hypothesis of normality. While this might be attributed to the potential nonlinearity in the data generation process, the normality assumption could not be rejected for the expenditures ratio of GDP; therefore suggesting the use of forecasting tools suitable for both linear and nonlinear linkages. Besides the linearity/nonlinearity, the choice of an appropriate forecasting model for time series is determined by the stationarity property of the variables as well as the optimum lag length. Panel B of Table 1 shows the unit root test results which indicate that both variables are non-stationary in levels, but of different order of integration. This justifies the decision to use ARIMAX as a benchmark, which implies further transformation to ensure stationarity before carrying out the forecasting analysis. The AIC information criteria points to the optimal lag length of 4; however, based on the correlation coefficient and partial correlation coefficient analysis recommended by Makridakis et al. (1998), it is determined that using the last quarter and the corresponding quarter from last year, (that is, t-1 and t-4) for lags was more effective for this analysis. Additionally, these two lags correspond with quarters of two subsequent years and the excellent model accuracy validates this choice, i.e. Q1 1970, and Q1 1971, etc.

Table 1. Descriptive statistics and unit root test results

Panel A. Summary Statistics	OADR	EXP/GDP
Mean	7.75439	25.0903
Maximum	10.4750	33.2000
Minimum	6.3937	16.3000
Std. Dev.	1.1151	3.1926
Skewness	0.7660	-0.2936
Kurtosis	2.3864	3.0058
Jarque-Bera	25.8730***	3.2767
Probability	0.0000	0.1643
observation	228	228
Panel B. Unit root test results	OADR	EXP/GDP
Level	-1.8292	-3.0884
First Difference	-2.5431	-6.1966***
Conclusion	I(2)	I(1)

Note. *** indicates significance at the 1% level of significance. The unit root test results are based on trend and intercept specification using the popular augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979 and 1981).

ARIMAX Versus DAN2 Results

For the sake of comparison, “identical” input values have been used for both models so as to ensure that changes, if any, can only be attributed to model specification. In addition, three main statistics are used to compare forecasting performance across models, namely the root mean squared error (RMSE), the mean absolute percentage error (MAPE) and the mean absolute error (MAE) referred to as accuracy. The first four observations are dropped on account of the lag length. The remaining 224 data points are divided into training and testing datasets. The study uses the traditional 80% (180 data points) for model training and the remaining 20% (44 data points) for model testing (hold out data). For DAN2, similar to other machine learning tools, once the learning engine is trained, the one-step ahead forecasting approach is used for the entire testing period. Although actual data was available, these actual values were not used to forecast ahead, instead it is used to measure model’s forecasted values for prior time periods to forecast for time t+1 for the entire testing period. This choice additionally contributes to model forecasting integrity. In practice, when actual data becomes available, inclusion of the actual data may further improve forecasting error for DAN2. Overtimes, when substantial new data becomes available, the existing trained engine can be recalibrated to account for any potential shift in process behavior.

Table 2. Forecasting output

Model	Training			Forecasting		
	RMSE	MAPE	MAE	RMSE	MAPE	MAE
ARIMAX	1.7337	5.85	94.15	3.1084	8.60	91.40
DAN2	0.7591	3.00	97.0	0.8483	3.14	96.9

Table 3. Forecast comparison

	Ye (DAN2)	*Ye (ARIMAX)*
Mean	25.2144	24.4315
Variance	8.39843	22.28216
Observations	224	224
Hypothesized Mean Difference	0	
Df	370	
t Stat	**2.1154***	
P(T<=t) two-tail	**0.0351**	
t Critical two-tail	1.9664	

Note. * indicates significance at the 5% level of significance.

Table 2 displays the forecasting performance of the two models. DAN2's results show an accuracy (MAE) value of 97% for both the training and testing data sets. The balance between the training and testing accuracy values are an indication of excellent model fit and the absence of overfitting. DAN2 outperforms ARIMAX by 5.5% point for the hold out (testing) data set. The improvement is statistically significant at 95% as indicated by the mean comparison test run on predicted outputs from both models (Table 3). Irrespective of the performance criteria used, DAN2 outperforms the ARIMAX benchmark across both training and testing periods; thus substantiating the superiority of DAN2 over traditional time series tools.

In sum, with an accuracy of about 97%, DAN2 represents a promising alternative for forecasting government expenditures. Moreover, the relatively good forecasting precision across models (ranging from 91% to 97%) confirms the casual role of population aging in predicting government expenditures in South Africa. Empirically, a number of factors including political, economic and demographic explain public spending growth; the relevance of which depends on the context (Borcherding, 1985; Peacock, 2004; Dizaji, 2014). The comparatively high prediction accuracy of government expenditures forecast after controlling for population aging might reveal the relative importance of demographic factors in driving public spending in South Africa. This finding implies that demographic monitoring is indispensable for efficient fiscal planning and management in South Africa.

PRACTICAL IMPLICATIONS AND POLICY RECOMMENDATIONS

Accurate public expenditure forecast is a crucial input to the government decision-making process. Various government decisions are likely to benefit from this research including those associated with planning, allocation, distribution and control. In the midst of constant political and economic turbulences coupled with changes in demographic structures, the management of public finance imposes a growing need of robust data governance frameworks to improve the decision-making process. In South Africa, policies and decisions are generally made in groups consisting of experts from a variety of fields; accounting for different perspectives and experiences. It is therefore not uncommon that decision making as group recommendations are subject to lengthy deliberations. While this process entails a minimum of prudence, decision making remains time consuming in South Africa. Evidence based inference can be used to improve this lengthy process; an exercise which requires accurate data that are not always easily available. The present study illustrates the use of machine learning- known as the most effective tool to roll out data lakes- to develop models for, and to carry out a sensitivity analysis on public expenditures forecasting in South Africa.

In addition, the study shows that population aging is an important predictor of public expenditures; suggesting that South African government should secure high budget for social protection and health, and if not possible, consider rationing some spending categories. Given the Covid-19 related contraction of the economy and the associated slow recovery, the latter option is more appropriate and could be achieved through a reform of the social benefits to older population. For example, the pension system can be restructured to accommodate reasonable payment delays necessary to mitigate the health care need of old households, at least to a limited extent. Two scenarios, therefore, can be recommended:

(1) The scale scheme scenario where pension income is partially paid depending on the pensioner's age; the resulting delay has the advantage to reduce the monthly aggregate pension bill. While the retirement age in South Africa is set at 64 years old, people with health conditions are permitted to retire from the age of 60 years. Beyond the 64-year threshold, capable retirees may take up part time employment up to the age of 70 years. Considering the flexibility in the vesting age (between 60 and 70 years), the scale scheme allows pensioners of similar income accumulation profile to benefit from different flow of monthly pension once retired; with younger retirees qualifying for less monthly payment.
(2) The second scenario consists of delaying the qualification age by offering incentives to postpone the retirement age, or encouraging some aging households into other income-generating alternatives in order to meet their growing financial needs.

These options can be evaluated to examine their validity and their implications. The model developed in this research is a framework for such a study. However, the use of machine learning algorithms for decision-making remains challenging in practice for many policy makers because these tools are still regarded as "Black box" (Jang, 2019). In addition, real-time data may not deliver comparable performance to that obtained from interpolated data used to test such algorithms. Despite these limitations, public spending forecast provides indications and quantifies the needs present in an aging population context. Therefore, more research should target technical advancement in the use of machine technique directed towards identifying best forecasting algorithms for various time span and frequencies.

CONCLUSION

This research introduced application of the machine learning approach to forecast government expenditures to support the population aging related increase in disease burden and pension spending in South Africa. The DAN2 machine learning system was employed to forecast South Africa's public expenditures using historical data from 1960-2016. The study used this dataset as input to DAN2 as well as a traditional modeling approach such as the ARIMAX. Results show DAN2-based model to outperform ARIMAX, validating that DAN2 is a promising tool for government expenditures forecasting. Both models used in this research deliver relatively high predictive accuracy implying that demographic development is an important predictor of government spending in South Africa.

While these findings emphasize the importance of demographic monitoring in achieving effective fiscal projections, to what extent demographic changes drive government spending remains an open question which is beyond the scope of this study. Finally, the finding of this research can assist economic decision makers to examine alternative policies and to use this model to evaluate the consequences of each policy.

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ENDNOTES

[1] According to Statistics South Africa (SSA), the number of beneficiaries has increased from under 3 million in 1997 to 11.8 million in 2007 and 17 million in 2017.

[2] This transformation is carried out in Eviews 10.

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