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Demographic Trends Forecasting: A Panacea for Sustainable Education Development Policies

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Abstract:
This paper presents a fuzzy time series methodology for forecasting demographic trends that could serve as a scientific approach toward a feasible and sustainable socio-economic development policies. In the experimental section, empirical analysis of population variation of Yobe State, Nigeria spanning over periods of 1996 – 2020 was carried out. The result revealed that FTS model can be used as an appropriate forecasting tool to predict population variations. It is expected that the findings of this research will benefit the present government's drive on education among other socio-economic conditions of Yobe State as the government declared a state of emergency in the basic and secondary education in the state on the occasion of its inauguration and swearing-in ceremony on 29th May, 2019.

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1. Introduction

In her pursuit to revitalise the education sector of the state, the Yobe State government declared a state of emergency in the education sector, with key interest in the basic and secondary education. Eventually, a technical committee was inaugurated and in the course of assessment of the current state of the education, the committee identified over-population of pupils in many primary schools among other challenges in the sector despite gruesome number of out-of-school pupils. The committee figure out forty percent out-of-school and 180 pupils per class as against the state adopted benchmark of 1:40 (Kabir, 2019). The notable scenario of this over-population is Arikime Primary School located in Potiskum town. The school has a population of over 15000 pupils, while the teacher student ratio stood at maximum of 1:370 as noted by (Dala, 2019) during the Yobe 1st Education Summit. He further pinpointed similar congestions in Moi Abali, and Moi Umar Primary Schools all in Potiskum town and the respective pupil population of the two schools are 10,300 and 10,700 as of the year 2019. This upsurge in the pupil's population in the basic education may not be unconnected with lack of demographic forecasting. Being an integral part of social-economic development, demographic forecasting allows us to assess the anticipated total population, the economically active population, the size of different age cohorts etc. (Sasu, 2010). These factors are essential in formulating meaningful, scientifically feasible and sustainable socio-economic development policies. Hence, forecasting of anticipated total population variation is inevitable and such forecasts may serve as a benchmark for socio-economic development policies if adequate mathematical and statistical tools for demographic analysis and modelling are employed. One such ideal tool in this regard is Fuzzy Time Series (FTS).

The concept of Fuzzy Time Series was built on the characteristics of fuzzy set theory, the theory was introduced by Zadeh (Ghosh et al., 2016; Alves et al., 2018) and it has been applied to several diverse areas (Sasu, 2010). Accordingly, Song and Chissom proposed the concept of FTS as noted in (Hosseini et al., 2011; Olatayo and Taiwo, 2014). Similarly, (Garg et al., 2013) noted that substantial work has been done on forecasting problems using fuzzy time series since it preposition. Areas such as university enrolments, stock index forecasting, market assets, economic indicators, exchange rate, electric load, temperature forecasting and tourism forecast are notable areas among many others that were subjected to fuzzy time series application over the years. Fuzzy Time Series forecasting methodology consists of defining universe of discourse (UOD), fuzzification of time series data points, assigning relationships between consecutive data points and defuzzification to get back the forecasting results in real domain (Pal & Kar, 2019).

2. Review of Literature

The method of Fuzzy Time Series in demographic forecasting in the recent years has been on the increase. For example, (Sasu, 2010; Abbasov and Mamedova, 2003; Bagirova et al., 2018) opined that fuzzy logic methods are used for population forecasts. On a general perspective, (Castanho et al., 2006) stated that fuzzy theory is also an alternative approach to study population changes. Additionally, (Diab and Saade, 2014) reported that the fuzzy model has been shown to fit well the population growth in some countries. Similarly, (Abbasov and Mamedova, 2003) observed that comparative analysis of the observed and forecasted data and the consequent error of the approximated method have confirmed the high efficacy of the fuzzy time series model while forecasting population. Furthermore, (Rustanuarsi and Abadi, 2018) successfully predicted the percentage of poor population in Indonesia with an accuracy rate of 94.34 percent.

To make the forecasting methodology and the data analyses self-acquainted, a reproduced summary of definitions of fuzzy time series concept found in (Song and Chissom, 1993; Chou, 2016; Garg et al., 2013; Lee and Chou, 2004; Sah and Degtiarev, 2005) are accordingly given as:

Definition 1

Let $Y(t)$ ($t = \ldots, 0, 1, 2, \ldots$), a subset of $\mathbb{R}^1$, be the universe of discourse on which fuzzy sets $f_i(t)(i = 1, 2, \ldots)$ are defined and $F(t)$ is a collection of $f_i(t)(i = 1, 2, \ldots)$. Then $F(t)$ is called fuzzy time series on $Y(t)(t = \ldots, 0, 1, 2, \ldots)$.

Definition 2

The universe of discourse $U = [D_L, D_u]$ is defined such that:

$D_L = D_{min} - t_{\alpha,n}\frac{s}{\sqrt{n}}$ and $D_u = D_{max} + t_{\alpha,n}\frac{s}{\sqrt{n}}$, when $n \leq 30$ or $D_L = D_{min} - z_\alpha \frac{\sigma}{\sqrt{n}}/\sqrt{n}$ and $D_u = D_{max} + z_\alpha \frac{\sigma}{\sqrt{n}}$, when $n > 30$;

Where: $t_{\alpha,n}$ is $100(1-\alpha)$ percentile of the t distribution,

z_α is $100(1-\alpha)$ percentile of the standard normal distribution

s & σ denotes sample and population standard deviations respectively.

D_{min} and D_{max} are respectively minimum and maximum values of the data in question

Definition 3

Let $F(t-1) = A_i$ and $F(t) = A_j$. Relationship between two consecutive observations, $F(t)$ and $F(t-1)$, referred to as a fuzzy logical relationship (FLR), can be denoted by $A_i \rightarrow A_j$ where A_i is called the left-hand side (LHS) and A_j is the right-hand side (RHS) of the FLR.

Definition 4

Assuming that there are m linguistic values under consideration, let A_i be the fuzzy number that represents the ith linguistic value of the linguistic variable, where $1 \leq i \leq m$. The support of A_i is defined to be:

$$\begin{cases} D_l + (i-1)\dfrac{D_u - D_l}{m}, \quad D_l + \dfrac{i(D_u - D_l)}{m}, 1 \leq i \leq m-1 \\ D_l + (i-1)\dfrac{D_u - D_l}{m}, \quad D_l + \dfrac{i(D_u - D_l)}{m}, i = m \end{cases}$$

Definition 5

If there exists a fuzzy relationship $R(t, t-1)$, such that $F(t) = F(t-1) x R(t, t-1)$, where symbol x is an operator, then $F(t)$ is said to be caused by $F(t-1)$. The existing relationship between $F(t)$ and $F(t-1)$ can be denoted by the expression $F(t-1) \rightarrow F(t)$

3. Methodology

The stepwise outline of the proposed forecasting process in accordance with the (Pal & Kar, 2019) description of fuzzy time series forecasting methodology is presented for the population variation (PV) values:

Step 1. Determine universe of discourse containing the extreme variation values in total population as, $U = [D_L, D_U]$

Step 2. Partition the universe of discourse U into several even and equal length intervals. Thus, $U = \bigcup_{i=1}^{m} u_i$, letting m the number of disjoint intervals.

Step 3. Determine the fuzzy sets A_i: some linguistic values represented by fuzzy sets of the interval of the universe of discourse such that its membership function is as follows:

$$u_{A_i}(x) = \begin{cases} 1 \; for \; x \in \left[D_l + (i-1)\frac{D_u - D_l}{m}, \quad D_l + \frac{i(D_u - D_l)}{m}\right), \\ \quad where 1 \le i \le m-1; \\ 1 \; for \; x \in \left[D_l + (i-1)\frac{D_u - D_l}{m}, \quad D_l + \frac{i(D_u - D_l)}{m}\right), \\ \quad i = m\,; \\ o \; otherwise. \end{cases}$$

Step 4. Then, $F(t) = A_i$, if $PV(t) \ni \text{supp}(A_i)$, where $\text{supp}(.)$ denotes support.

Step 5. Identify fuzzy linguistic relationships (FLR's) among linguistic time series values, $A_i \to A_j$.

Step 6. Establish fuzzy relationship groups (FLRGs): identification of $A_i \to A_j$ (FLR's) having the same LHS.

Step 7. The proposed forecasting rule for the PV data set at time t is as follows:

a) Let $F(t) = A_i$

a) Select FLR groups where fuzzy value A_i is a transition.

b) Define: 1) $\bar{u}_{11} = \frac{1}{l}\sum_{i=1}^{l}\bar{u}_i$

2) $\bar{u}_{21} = \frac{1}{l}\sum_{j=1}^{l}\bar{u}_j$

where: $\bar{u}_i$ is the mid-point of the left ith FLR,

$\bar{u}_j$ is the mid-point of the right jth FLR and

$l \le m$

c) Let $\mu_{(t)}^{p} = (\bar{u}_{11}\;\bar{u}_{21})^T$, a $(2\;x\;1)$ matrix,

Thus, the in-sample forecast value is:

$\hat{P}v_t = \frac{1}{2}(X\mu_{(t)}^{p})$, such that X, is an $(1\;x\;2)$ matrix with unit elements.

Similarly, for the out of sample forecast $(t+1)$, define:

$\hat{P}v_{t+1} = \frac{1}{2}(X\mu_{(t)}^{p})(1+r)$,

where r is the annual population growth rate.

Step 8. Forecast evaluation

4. Experimental Results

To test the proposed model, empirical analysis of the 24 records of the population variation (PV) values data set is demonstrated in this section in accordance with the outlined procedures presented in section 3. A comparative assessment of the forecasted values alongside the observed records is given at the end of this section. Additionally, the evaluation of the proposed model both in terms of comparative analysis and performance metric (MAPE) is also reported.

Onward in the section, let PV represent the population variation values data set. Descriptive analysis over the PV produces the following statistics: $s = 27.416$, $PV_{min} = 48.117$, and $PV_{max} = 130.326$. The empirical demonstration is as follows:

Step 1. From definition 2, the universe of discourse $U = [D_L, D_u]$, since $n < 30$, a $100(1-\alpha)$ percentile of the student's t-distribution is considered. Therefore ,letting $\alpha = 0.05$, $t_{0.05,24} = 1.711$, $D_L = PV_{min} - t_{\alpha,n}\frac{S}{\sqrt{n}} \cong 38.549$ and $D_u = PV_{max} + t_{\alpha,n}\frac{S}{\sqrt{n}} \cong 139.894$. Thus, $U = [38.549, 139.894]$.

Step 2. The partitioning of the universe of discourse into m even and equal length intervals is as follows: m is set to 7, because it is the usual practice as noted in (Ghosh et al., 2016). Therefore, $u_1 = [38.549, 53.027)$, $u_2 = (53.027, 67.505)$, $u_3 = (67.505, 81.983)$, $u_4 = (81.983, 96.461)$, $u_5 = (96.461, 110.939)$, $u_6 = (110.939, 125.417)$, and $u_7 = (125.417, 139.895]$.

Step 3. It is tenable in the literature that 'the variation in total population' is a linguistic variable that assumes the following values:

A_1 = (very low level population growth (VLLPG))

A_2 = (low level population growth (LLPG))

A_3 = (changeless population growth (CPG))

A_4 = (moderate population growth (MPG))

A_5 = (normal level population growth (NLPG))

A_6 = (high level population growth (HLPG))

A_7 = (very high level population growth (VHLPG))

The membership function of these linguistic values is given as:

$$u_{A_i}(x) = \begin{cases} 1\ for\ PV \in [38.549 + (i-1)(14.478),\ 38.549 + i(14.478), \\ where 1 \le i \le m-1; \\ 1\ for\ PV \in [38.549 + (i-1)(14.478),\ 4.220 + i(14.478)], \\ i = m; \\ 0\ otherwise. \end{cases}$$

Hence, the supports are: $\sup(A_1) = [38.549, 53.027)$, $\sup(A_2) = (53.027, 67.505)$, $\sup\ (A_3) = (67.505, 81.983)$, $\sup\ (A_4) = (81.983, 96.461)$, $\sup\ (A_5) = (96.461, 110.939)$, $\sup\ (A_6) = (110.939, 125.417)$, and $\sup\ (A_7) = (125.417, 139.895]$

The mid-points of the intervals computed as average of the lower and upper limits of each linguistic value are obtained as: $\bar{u}_1 = 45.788, \bar{u}_2 = 60.266, \bar{u}_3 = 74.744$, $\bar{u}_4 = 89.222, \bar{u}_5 = 103.700, \bar{u}_6 = 118.178$ and $\bar{u}_7 = 132.656$.

Step 4. The Fuzzy time series F(t) on PV_t is A_i, if $PV_t \in \text{supp}(A_i)$. Thus, $(1997) = A_1$, $F(1998) = A_1, \ldots, F(2020) = A_7$. These transformation of the PV_t into fuzzy values is given in table 1.

Step 5. In accordance with definition 3, the Fuzzy Logical Relationships are as follows: $A_1 \rightarrow A_1, A_1 \rightarrow A_1, \ldots$ and $A_7 \rightarrow A_7$ as shown in Table 1.

Table 1: Actual and Fuzzified Population Variation Values

Year	Population	PV '000'	Fuzzified PV	FLRs	Year	Population	PV '000'	Fuzzified PV	FLRs
1996	1609274				2009	2578336	88.681	A_4	$A_4 \rightarrow A_4$
1997	1657391	48.117	A_1		2010	2670175	91.839	A_4	$A_4 \rightarrow A_4$
1998	1706947	49.556	A_1	$A_1 \rightarrow A_1$	2011	2765286	95.111	A_4	$A_4 \rightarrow A_4$
1999	1757985	51.038	A_1	$A_1 \rightarrow A_1$	2012	2863785	98.499	A_5	$A_4 \rightarrow A_5$
2000	1810549	52.564	A_1	$A_1 \rightarrow A_1$	2013	2965792	102.007	A_5	$A_5 \rightarrow A_5$
2001	1864503	53.954	A_2	$A_1 \rightarrow A_2$	2014	3071433	105.641	A_5	$A_5 \rightarrow A_5$
2002	1920065	55.562	A_2	$A_2 \rightarrow A_2$	2015	3180836	109.403	A_5	$A_5 \rightarrow A_5$
2003	1977283	57.218	A_2	$A_2 \rightarrow A_2$	2016	3294137	113.301	A_6	$A_5 \rightarrow A_6$
2004	2036206	58.923	A_2	$A_2 \rightarrow A_2$	2017	3411473	117.336	A_6	$A_6 \rightarrow A_6$
2005	2096885	60.679	A_2	$A_2 \rightarrow A_2$	2018	3532989	121.516	A_6	$A_6 \rightarrow A_6$
2006	2321591	224.706	A_4	$A_2 \rightarrow A_4$	2019	3658833	125.844	A_7	$A_6 \rightarrow A_7$
2007	2404024	82.433	A_4	$A_4 \rightarrow A_4$	2020	3789159	130.326	A_7	$A_7 \rightarrow A_7$
2008	2489655	85.631	A_4	$A_4 \rightarrow A_4$					

Note 1: The 2006 PV is considered as an outlier, hence, replaced with the median variation.

Step 6. From the FLRs identified in step 5, ten FLR groups were derived by identifying FLRs having the same LHSs. These ten groups are as follows: $G_1: A_1 \rightarrow A_1$,

$G_2: A_1 \rightarrow A_2$, $G_3: A_2 \rightarrow A_2$, $G_4: A_4 \rightarrow A_4$, $G_5: A_4 \rightarrow A_4$, $G_6: A_4 \rightarrow A_5$, $G_7: A_5 \rightarrow A_5$, $G_8: A_5 \rightarrow A_6$, $G_9: A_6 \rightarrow A_6$ and $G_{10}: A_6 \rightarrow A_7$.

Step 7. Now applying the forecasting rule: for example, for $t = 1997$, F(1997) $= A_1$. Then, the FLR groups A_1 being a transition are G_1 and G_2. Thus, $\bar{u}_{11} = 45.788$, $\bar{u}_{21} = 53.027$, $\mu^p_{(1997)} = \begin{pmatrix}45.788\\53.027\end{pmatrix}$, $X = (1 \quad 1)$. Hence, the forecasted value at t = 1997 is:

$\hat{P}v_{1997} = \frac{1}{2}\left((1 \quad 1)\begin{pmatrix}45.788\\53.027\end{pmatrix}\right) = 49.408$. Similarly, for t = 2001, F(2001) $= A_2$. G_2, G_3 and G_4 are the FLR groups A_1 being a transition. Thus, $\bar{u}_{11} = 55.440$, $\bar{u}_{21} = 69.918$, $\mu^p_{(2001)} = \begin{pmatrix}55.440\\69.918\end{pmatrix}$, $X = (1 \quad 1)$. Hence, the forecasted value at t = 2001 is: $\hat{P}v_{2001} = \frac{1}{2}\left((1 \quad 1)\begin{pmatrix}55.440\\69.918\end{pmatrix}\right) = 62.679$

The forecasted results based on the forecasting rule for the periods in question are presented in Table 2.

Table 2: Actual and Forecasted Population Variations

Year	Population	Actual PV ('000' Persons)	Forecasted PV ('000' Persons)	Year	Population	Actual PV ('000' Persons)	Forecasted PV ('000' Persons)
1996	1609274			2009	2578336	88.681	86.809
1997	1657391	48.117	49.408	2010	2670175	91.839	86.809
1998	1706947	49.556	49.408	2011	2765286	95.111	86.809
1999	1757985	51.038	49.408	2012	2863785	98.499	103.7
2000	1810549	52.564	49.408	2013	2965792	102.007	103.7
2001	1864503	53.954	62.679	2014	3071433	105.641	103.7
2002	1920065	55.562	62.679	2015	3180836	109.403	103.7
2003	1977283	57.218	62.679	2016	3294137	113.301	118.178
2004	2036206	58.923	62.679	2017	3411473	117.336	118.178
2005	2096885	60.679	62.679	2018	3532989	121.516	118.178
2006	2321591	90.260	86.809	2019	3658833	125.844	125.417
2007	2404024	82.433	86.809	2020	3789159	130.326	125.417
2008	2489655	85.631	86.809				

Step 8. Forecast evaluation

Statistical measures of the actual and forecasted population variations were presented in Table 3 in order to evaluate the performance of the proposed model. It is apparent that the actual and forecasted values statistics are approximately equal with a slight difference at some instances. A pictorial comparison of these measures and the actual and forecasted population variations trends are respectively shown in Figure 1 and Figure 2 to further highlight the accuracy of the proposed model. Furthermore, the MAPE value consolidated the suitability of the proposed model for forecasting as the value of the metric is nearly within ten percent error, which is an indication of high accuracy as noted by (Bakawu, Abdulkadir, & Maitoro, 2020).

Table 3: Actual and forecasted population variations descriptive statistics

Measures	MIN	MAX	MEAN	STD
Actual	48.117	130.326	85.227	27.416
Forecast	49.408	125.417	85.502	25.993

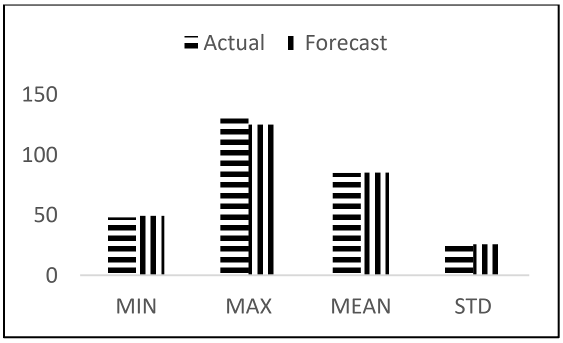

Figure 1: Bar chart of the actual and forecasted PV Descriptive Statistics

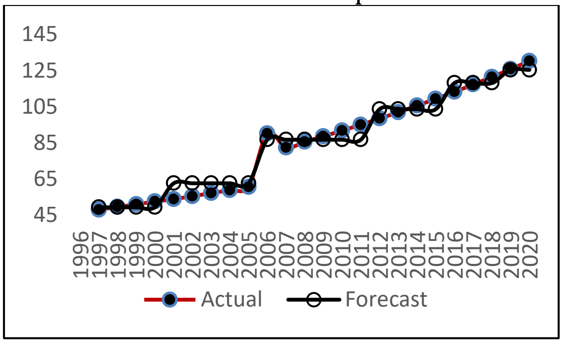

Figure 2: Trend of the actual and forecasted population variations

5. Conclusion

The dynamics of annual population variations of Yobe State, Nigeria has been studied in this article using FTS for the purpose of enhancing feasible and sustainable socio-economic development policies in the state. The population data used for the empirical analysis were sourced from Annual Abstract of Statistics made available in (National Bureau of Statistics, 2006; National Bureau of Statistics, 2012; National Bureau of Statistics, 2017) for the periods 1996 – 2016; while for the periods 2017 – 2020, an exponential projection model of the National Bureau of Statistics was adopted for generation of the population. The projection is based on the 2006 population and the annual growth rate: an index that is provided by the National Bureau of Statistics for each state in Nigeria (Zakariya, 2020). Yobe State has an annual population growth rate of 0.035. The study reveals that FTS model can be used as an appropriate forecasting tool to predict population variations. Hence, the author suggest that the population variations prediction may be considered as a reference point for socio-economic development policies. However, caution must be taken in applying the proposed model as it may be bias as a result of incorporation of population projections.

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