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DEVELOPMENT OF DELTA STATE POPULATION CENSUS FORECASTING OF NATURAL GROWTH MODEL OF ORDINARY DIFFERENTIAL EQUATION USING PYTHION PROGRAMMING

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Abstract

The paper focuses on the development of Population Forecasting using the Natural Growth Model of Ordinary Differential Equation of First Order of Scipy Python, specifically for the Delta State Population Census 2006. The study compares manual estimation integration methods results with the Python Scipy library and visualizes population predictions using graphs and bar charts. The Average performance accuracy of 98 percent of the prediction of Delta State Population Model of Natural Growth Model of Ordinary Differential Equation of First Order of Scipy Python

***Keywords**: Natural Population; Model of Ordinary Differential of Scipy Python; Integration Method; Prediction of Population Model and Forecasting*

1 Introduction

Forecasting refers to the prediction of a given population as a result of child birth and death rate of humans or animals in a given community, state, and country at large. Population forecasting is done to know the actual population of females and males to distribute infrastructure and social amenities per the resources available at a given time. Population forecasting is challenging and must come to fruition by the utilization of established models. According to [2], there are three methods for predicting demographic processes: extrapolation, expectation (birth expectations at the individual or expert opinions at the population level), and theory-based structural modeling using exogenous factors. Three parameters are included in the models: age, period, and cohort. Multistate models, such as macro-simulation and micro-simulation, also employ decomposition and disaggregation. It is challenging to predict changes in the demographics; accuracy varies depending on the specific circumstances or patterns, and it is unclear when a strategy would work best. Estimation is highly uncertain; estimates of uncertainty (ex-ante error based on expert opinion, ex-post error based on models, and in Timex post error) disagree. Random scenarios or stochastic population renewal serve as the foundation for probabilistic population forecasts. Approaches that complement one another are pointedly being used more and more. Population census is the basis of population forecasting. Population census refers to regular and simultaneous house-to-house enumeration by the government or its agent regarding all persons, that is, beggars, abled and disabled, children, men, and women who live in a particular area at a given period. The vital features of a good population according to the 2006 census as reported by the National Population Commission are listed as follows: it must be carried by the government or its agents and not private individuals or organizations; It must divulge the population of a specific territory at a particular point in time; it must be a regular or periodic count that should be taking place at regular interval of say 5, 10, 20 years, etc. This becomes necessary to determine the population growth of the females and males and to know where there are inadequate social amenities and to provide. This is also to determine the density of the thickly and sparsely populated areas,

1.1 Related Literature

The article summarizes developments, evaluates advancements, and looks ahead. In [7], Period life table measurements have served as the foundation for the author's discussion of how they approached the research of population aging. Although this was required to convey their main ideas clearly, it is far too restrictive. Firstly, a cohort life table may also be employed; but, of far greater significance, a variety of individual attributes can be employed to investigate population aging through the application of

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techniques outlined in this work. You may find more thorough explanations of how to use the methods in references [12], and [13]. The contrasts between results based on cohort life tables and period life tables are analytically discussed in [11].

Hare et al. [4], state that the mechanistic hypothesis underlying their model is that juvenile mortality in their estuarine habitats throughout the winter is driven by temperature. This results in recruitment. Fourteen general circulation models that simulated three CO2 emission scenarios were used to forecast temperatures. To predict the population's response, an ensemble-based method was employed, wherein a multi-model average was computed for a specific CO2 emission scenario. The linked model shows that the number and distribution of Atlantic croakers are severely impacted by both climate change and exploitation. The average spawning biomass of the population is predicted to increase by 60–100% between 2010 and 2100 at present fishing levels. In a similar vein, it is predicted that the population center will move 50–100 kilometers northward. According to a yield study, which sets benchmarks for fishery management, there will be a 30-to 100% rise in the maximum sustainable production. The authors' findings showed that to achieve sustainable exploitation in a changing climate, managers need to be aware of, comprehend, and take into account the consequences of climate change on fisheries.

Using population models and connected AOPs parameterized using long-term white sucker (Catostomus commersoni) monitoring data gathered from a study site at Jackfish Bay, Lake Superior, Canada, the authors illustrated their approach. The ability of the framework to predict changes in population status, both in terms of ongoing impact and subsequent recovery after stressor mitigation associated with process changes at the mill, was demonstrated by the individual responses of fish exposed to pulp mill effluent [8]. The authors compiled 2379-time series of vertebrate population indices from real surveys to examine the effectiveness of time-series forecasting models for wild animal population data. Their data were of three very distinct types: small variance but long memory (bird and animal counts), strongly cyclic (adult salmon counts), and extremely variable (marine fish production). Autoregressive time-series models, non-linear regression-type models, and non-parametric time-series models are the three main kinds of forecasting models that the researchers assessed for predictive performance. Over a broad variety of taxa, low-dimensional parametric autoregressive models produced the most accurate forecasts; the most accurate model was one that merely used the most recent observation as the forecast [14].

Zylstra [17] forecasts of how populations will react to climate change are becoming more and more important to conservation plans for threatened species. For these projections to be correct, they need to take into consideration a variety of sources of uncertainty, such as those related to future climatic scenario projections and those related to population dynamics models. The majority of population predictions ignore the significance of assessing uncertainty in the population model's structural design, even if many of them take parameter uncertainty in abiotic effects and process variance related to unexplained temporal variation into account. [5] showed that density-dependent mechanisms are anticipated to worsen the negative effects of climate change and diminish the population viability of this keystone species by accounting for structural uncertainty in a model of blue mussel population expansion. The aforementioned results underscore the significance of integrating structural unknowns into population projections and the worth of methodologies that consider various origins of climate and model uncertainties.

To anticipate the population in China, this research develops a BP neural network model that exhibits good prediction accuracy and can be applied to population forecasting in the future. MATLAB software is used to train and simulate the model, which is based on demographic data from China from 1961 to 2021. The population of China in 2022 is predicted by the trained model, which serves as a useful guide for relevant departments' decision-making [15]. It was discovered that the Time Independent Fourier Amplitude Model Approach was a good model for population prediction when it came to projecting the US population from 1790 to 2020 and beyond. The outcomes from various models, including the Malthusian, Logistics, and Logistics (Least Squares) Models, were compared with the findings from the time-independent Fourier Amplitude Model Approach. The sum of square error (SSE) and the coefficient of determiner (R) were used to assess the models' quality of fit.

However, [1], the forecasting of Nigeria's Population census used a natural growth model, and the geometric model method was estimated using a visual basic programming approach which leads to a delay of time in obtaining desirable results. Due to this fact in this research paper Python programming language that gives fast results in computation will be utilized.

1.2 Research Objective

The main objective of this research is the development of Population Forecasting of Delta State using the Natural growth model of the ordinary differential equation of Scipy Pythion. The specific objectives are: To generate manual estimation using the natural growth model; to compare the result of manual estimation with the python Scipy library; to visualize the result of the prediction of Population with graph and bar chart; to evaluate the Population Area under Curve of Integration Method for Delta State

2 Research Methodology

2.1 Data Collection Method

The data utilized as a source of input to generate the output of forecasting population were collected from the National Population Commission of Nigeria, Abuja based on 2006 census data of various States. The initial Delta State Population Census of 2006 is 4112445; of this number, the male population was 2043156, and the female population was 2069309.

Model

Mathematical modeling is an interactive process that encompasses the interdisciplinary interaction of the art of science. The art deals with intuitive reasoning at various stages. For this research, the model adopted is the Natural Growth Model of Ordinary Differential Equation of First Order which is stated as:

$\int dQ/dt=KQ$ (1)

K is the rate of constant of childbirth and death rate in Delta State based on the 2006 Population Census.

t is the number of years

Q is the initial total population of the 2006 census for the Male and Female Population

$\int dQ/Q=K\int t\,dt$

$InQ=Kt + C$

Take a log of both sides

$Q = C\,e^{kt}$

If the initial population of Delta State $C = Q_o$

$Q = Q_o\,e^{kt}$ (2)

If the constant population rate of growth for birth and death is 3.8% ie 0.038

$K = 0.038$

$Q = Q_o e^{0.038t}$ (3)

Where Q_o is the initial population of Delta State Population Census, including Males and Females.

For the female population let it be F

$Q_f = F_o e^{0.038t}$ (4)

Equation (4)is for the computation of the female population of Delta State.

The male population, let it be M

$Q_m = M_o e^{0.038t}$ (5)

The equation (5) is for the computation of the male population of Delta State.

Where M_o is 4112445 is the initial population of the male and female population of Delta State Census 2006.

$Q = 4112445e^{0.038t}$ (6)

From equation 1 to 6 are based on the population census from 2006 to 2015 of males and females with an increasing rate of 3.8%, that is, a constant of 0.038 used to evaluate the projection from 2006 to 2015 which is 10 years. The initial Delta State Population Census of 2006 is 4112445while the male population was 2043156 and the female population was 2069309. The computed values of the male and female population predicted using equations 1 to 6 are tabulated in Table 1.1.

Table 1. Manual Computation using Natural Growth Method
STATE POPULATION CENSUS FORECAST 2006 TO 2015

YEARS	POPULATION	MALE	FEMALE	RATE
2006	4112445.00	2043156	2069309	Nil
2007	4437139.27	2232324.771	2204814.499	0.038
2008	4608976.994	2318776.326	2290200.668	0.038
2009	3787469.492	2408575.902	1378893.59	0.038
2010	4972874.495	2501853.158	2471021.337	0.038
2011	5165459.703	2598742.777	2566716.926	0.038
2012	5365503.186	2699384.653	2666118.533	0.038
2013	5573293.78	2803924.101	2769369.679	0.038
2014	5799131.51	2912512.063	2886619.447	0.038
2015	6013328.018	3025305.326	2988022.692	0.038

2.2 Implementation of Population Forecast of Delta State Using Python Programming

The Python code of Ordinary differential equation model to generate the Population Forecasting of Delta State Census from 2006 to 2015. The population growth constant rate of 3,8 percent, which is 0.038. This is done by importing the NumPy library, Scipy integration, and Matplot library module
The ODEINT (Ordinary Differential Equation Integration) library is a collection of advanced numerical algorithms to solve the initial value problem of differential equations. Y0 initial population of Delta State in 2006 population census

```
In [1]:  import numpy as np

In [2]:  from scipy.integrate import odeint

In [3]:  from matplotlib import pyplot as plt

In [4]:  k=0.3

In [5]:  def model(y, t):
             k=0.3
             dydt = k*y
             return dydt
```

Figure 1

The ordinary differential equation model is shown in Figure 1.

3 Prediction of Population Census of Delta State

This module is for the generation of prediction and forecast of the total population of Delta State from the Scipy library from 2006 to 2015, that is decade.. this involves array creation with the initial population of Delta State population census of 4112445 to give the desirable results as in Python generated code.

```
In [8]:  t = np.arange(0,10,1)

In [9]:  y0 =4112445

In [10]: y = odeint(model,y0,t)

In [11]: print(t)
         [0 1 2 3 4 5 6 7 8 9]

In [17]: print(y)
         [[4112445.        ]
          [4459415.64730506]
          [4835660.53389283]
          [5243649.59030177]
          [5686060.97805623]
          [6165799.043368  ]
          [6686013.04711411]
          [7250117.97168475]
          [7861817.0605995 ]
          [8525125.64304586]]
```

Table 2 Population Prediction of Delta State Census.

Number	Years	Predicted Population
1	2006	4111445
2	2007	4459415.
3	2008	4835660
4	2009	5243649
5	2010	5686060
6	2011	6165799
7	2012	6686013
8	2013	7250117
9	2014	7861817
10	2015	8525125
Total Population Predicted		60825100

The population of Delta State Forecasted from 2006 to 2015 as generated by Matplot of Python module. This depicted the graphical represented in Figure 2 below.

```
In [18]: for i in t:
             if i==10 or i==20:
                     k=int(i)
                     print('The population after'+ str(i)+'years is:' + str(y[k]))
         plt.plot(t,y)
         plt.plot(t,y,'ro')
         plt.xlabel('time in years')
         plt.ylabel('population of Delta State')
         plt.title('population of Delta State(k=0.038)')


         plt.show()
```

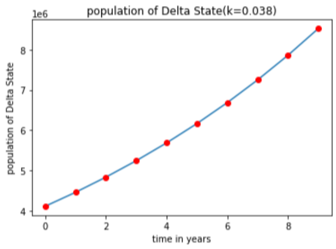

Figure 2. A Graph of Population of Delta State against Time Years.

Figure 2 depicts a graph of the Population of Delta State against Time years in a geometric progression. That means that the population has grown exponentially, from the year 2006 to 2015.

The Scipy library performs the following functions in the natural growth model of first-order differential equations in population forecasting in the Python program.

1. **ODEINT:** Solves the initial value problem for the first-order differential equation of population growth.
2. **exp:** Calculates the exponential function, essential for modeling population growth.
3. **linspace:** Generates an array of time points for which population sizes are calculated.
4. **plot:** Visualizes the population growth with the prediction values of Population of Delta State Population Census and curve using Matplotlib.
5. **optimize:** Estimates model parameters, such as growth rates, from empirical data and gives the prediction values of Population of Delta State Population Census.
6. **curve_fit:** Fits the population growth model of Delta State Population to empirical data.
7. **interp1d:** Interpolates population sizes at specific time points.
8. **integrate. quad:** Calculates the area under the population growth curve, representing total population size or cumulative population growth.

Scipy's functions enable the numerical solution, visualization, and parameter estimation of the natural growth model, facilitating population forecasting and analysis.

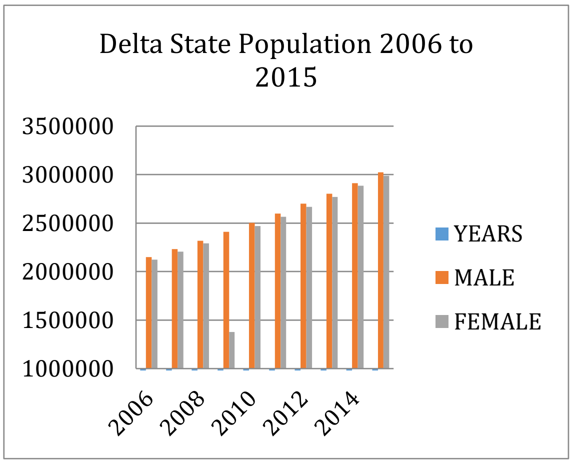

Figure 3.0 Bar for the population set.

The figure above indicates the various population projections from 2006 to 2015

Figure 3.0 above shows the Delta State Population of males and females from 2006 to 2015 in the Bar Chart. The Male population outclassed the female population as demonstrated in the bar chart.

Integration Method of Population Estimate of Area Under Curve of Delta State Population.

As from equation (6) the model of population is stated as

$$\int_0^{10} 4112445e^{0.038t} \qquad (7)$$

The zero (0) is called the lower bound while the 10 is called the upper bound of the population of Delta State Population under the curve in the equation(7).

When the equation (7) is integrated with

The area under of curve of the Population of Delta state in Figure 2 originates from a range of zero to 10 years, it gives this result:

$=(4112445e^{0.038X10} - 4112445e^{0.038X0})/0.0038$

= 50023238

The Area of Population of Delta State under the Curve is 500232138 by integration method.

$Population\ of\ Delta\ State$= The Area of Population of Delta State under the Curve

The population of Delta State=50023238

Percentage error = $\frac{/\text{actual – Predicted} \ /}{actual\ value}\ X\ 100$ equation (8), compute the percent error of the Population of Delta State.

$= \frac{/50023238-60825100/}{50023238}\ X\ 100$

=21 Percent

Average Percent Error= Percent error of Population of Delta State divided by the number of years Equation (9)

=2.1 percent

Average Performance =100-2.1percent Equation (10). This will eventually give the result of the Average Performance of the Natural growth model of Delta State Population.

=97.9 percent

=98 Percent.

This result is desirable and shows that Scipy Python of Natural Growth Model of Population of Delta State Census prediction is in tandem with the integration method as far as the error involved is negligible.

4 Conclusion

The paper actualized the visualized result of the prediction of the Population of Delta State with the graph in Figure 2 and a bar chart to see the trend of prediction of female and male population trends of Delta State as depicted in Figure 3. The Average performance accuracy of 98 percent of the prediction of population model of Natural Growth Model of Ordinary Differential Equation of First Order of Scipy Python. The paper contributed to the body of knowledge by coming up with the Population Prediction Model as stated in equation 6 and the Population Area under the curve of integration method for Delta State in equation 7 obtained from figure 2 which can be utilized for forecasting and prediction of Delta Stat\e Population Census. This model can be modified and adopted by researchers for population forecasting and prediction of other states to ease documentation. Further research should gear towards more years of prediction and forecasting instead of 10 years, In light of the above, the area under the curve estimation should include trapezoidal and Simpson's rule method of integration method.

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