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Numerical Modeling of Population Growth in Kedah

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ABSTRACT

Population growth modeling requires mathematical methods to simulate data for more effective planning and decision-making related to issues such as socioeconomic development, environmental sustainability, resource allocation, manpower, and more. In line with these concerns, a state like Kedah also needs well-aligned development plans that reflect its population trends. Due to the high cost of conducting census exercises, this study employs various mathematical models namely exponential model, third order polynomial regression, and Runge-Kutta fourth order (RK4) method to estimate and predict the future population growth of Kedah. The three models are compared with one another and validated against actual population data and projections from the Department of Statistics Malaysia (DOSM) for the period 1970 to 2060. The best-performing model is identified based on its R-squared value, where a value approaching 1 indicates high accuracy and model significance. The results conclude that the RK4 method is the most accurate with an R-squared value of 0.99921329.

Keywords: population growth, polynomial regression, exponential model, Runge-Kutta fourth order

1 INTRODUCTION

Demographically, Malaysia experienced a significant transition in population growth patterns over the past several decades. The high rates of population growth in Malaysia of 3.2% per year in 1960-1963 had reduced to 2.3% annually during 1975–1980, reflecting the early effects of urbanization, increased female labor force participation, and expanded access to education and family planning services [1]. Interestingly, growth rebounded slightly to 2.6% per year in 1980–1985, due to the National Population Policy introduced in 1982 to achieve a 70 million population by 2100. This policy encouraged larger families and led to a temporary surge in population growth, reaching 2.9% annually during 1985–1990. However, the effect of the new policy on childbearing was short-lived, as the rate of population growth quickly took a downturn to reach 2.4% per annum in 1995-2000, and further to 1.8% per annum in 2005-2010, despite significant immigration flows, particularly of foreign laborers, that partially offset the slowing natural increase [1], [2]. This is probably due to the decline in the fertility rate from 1982 until 2019, with the current fertility rate of 1.983 births per woman [3]. Based on Figure 1, from 2010 until 2024, the population growth has shown decreasing patterns with the lowest peak being -0.2% in 2020 then increasing slowly until 2024 with 2.0% growth. As of 2025, the estimated total population of Malaysia is 34.2 million, with demographic composition remaining relatively stable: 69.4% Bumiputera (inclusive of Malays and other indigenous groups), 23.2% Chinese, 6.7% Indian, and 0.7% other ethnicities [4]. This demographic evolution is reflective not only of Malaysia's success in implementing health, education, and family planning reforms but also the broader global shift experienced by many developing nations transitioning into middle-income economies. Scholars such as [5] and [6] argue that declining fertility in Southeast Asia is closely tied to increased female educational attainment, delayed marriage, urban cost-of-living pressures, and shifting social norms regarding ideal family size. Malaysia is no exception to these trends, as evident in the growing policy focus on managing aging, sustaining workforce productivity, and ensuring equitable development amid changing population dynamics.

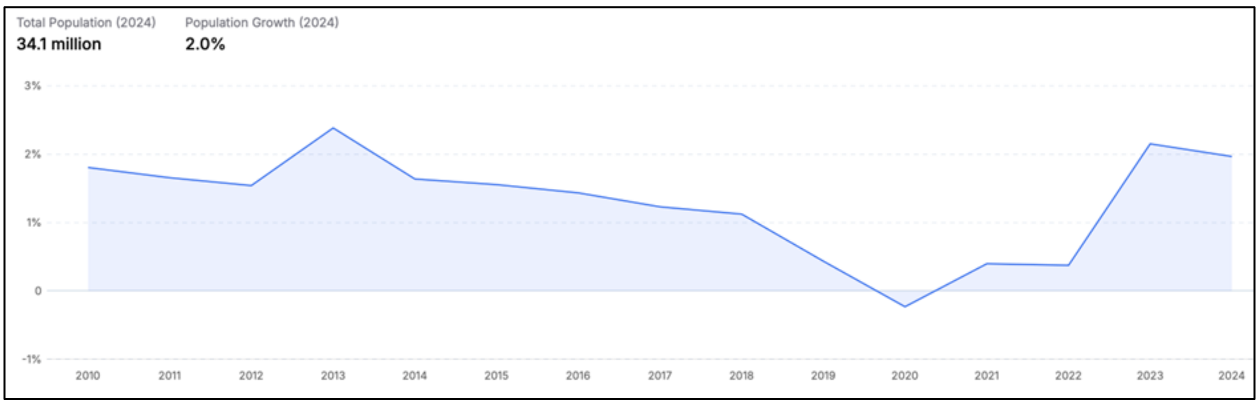

Figure 1: Malaysia's population growth.
Source taken from the website of Department of Statistics Malaysia (DOSM) [4]

Previously, population data was recorded through the census exercise that have significant challenges worldwide, including high costs, concerns about privacy and intrusiveness, declining response rates, and other logistical issues [7]. As a more cost-effective alternative, many previous studies have employed various mathematical models to estimate and predict future population growth. Mathematical modeling is the process of representing real-world phenomena using mathematical equations, often requiring computational techniques to simulate the behaviour of the model such as in population growth modeling. Mathematical models can project the total population data by using the previous recorded data and the famously known such models are exponential and logistic. The exponential growth model was proposed by Malthus in 1798 where the model suggests that the growth is exponential and has no bound while the logistic growth model was proposed by Verhulst in 1845 with the inclusion of the limiting value (called carrying capacity) which is the size of population that an environment can support [8]. Most of the successful models are based on the extended forms of these models, including generalized logistic models, Gompertz models, stochastic growth models, and agent-based simulations, which are capable of incorporating additional demographic variables such as migration, fertility rate changes, age structure, and policy impacts [9], [10]. The application of such models is critical not only for projecting future population sizes but also for simulating demographic transitions, anticipating urban infrastructure needs, and supporting evidence-based governance. In the context of Malaysia and other developing countries, these models provide insight into the implications of declining fertility rates, aging populations, and the role of migration in shaping future demographic landscapes.

Population research goes far beyond the collection of demographic data, as highlighted by [11] and [12]. It is also inherently tied to the availability of resources and labor demand, both of which impact social, economic, political, and environmental development in an area. With the ongoing socio-economic and demographic growth, it is essential for Malaysia to ensure planning for development is based on population trends. Planning and development strategies, such as the Malaysia Plan, the National Policy for Older Persons, and the National Urbanisation Policy, must incorporate demographic factors to foster sustainable development, social equity, and inclusive growth. Attaining these goals becomes extremely difficult without a well-informed understanding of population trends over time.

Mathematical models of populations provide a scientific foundation for projecting future problems and synchronizing national goals with demographic realities. Traditionally, mathematical models, especially exponential and logistic models, have been used as a means to analyze, evaluate, and forecast population growth. Numerous studies support the validity of the logistic model for forecasting because of its elements of environmental limits. For example, [13], [14] applied the logistic model using census data for Rwanda (1980–2008) and Uganda (1980–2010) and in both instances the logistic model produced forecasts consistent with census data. Also, [15] illustrated that logistic based models offered more accuracy than exponential and autoregressive modeling in Jordan (1955–2016) as it provided reliability of long-term projections. [16] using census data from the Philippines (1960–2015) confirmed the reliability of long-term projections using logistic modeling and regression methods while predicting the limitations of simple approaches like exponential, hyperbolic and Gompertz models. However, the use of the best model was reliant on the regional population. [17] showed that the exponential model provided a higher R-squared value for Taraba State, Nigeria (1991-2019) population forecasting, indicating it offered more reliability than logistic models. Likewise, [8] using census data from 1967 and 2012, they projected Tanzania's population to grow at 2.88% annually, reaching about 67.6 million by 2035 under the exponential model. Therefore, logistic models are more reliable for long-term forecasts, but exponential models can provide greater accuracy for short-term predictions in certain regions.

Moreover, regression-based methods like polynomial regression have been introduced to account for nonlinear patterns of population growth. Polynomial regression is an extension of simple linear regression that includes higher order terms as additional variables, making it an excellent tool for fitting higher order data trends that are either curvilinear or periods of increasing growth, for example, quadratic and cubic trends. Research has shown polynomial regression can provide reasonable approximations when the population growth is not strictly exponential or strictly logistic, thus it allows greater flexibility for medium-term forecasts (see [18], [19]).

Recent advancements in demographic forecasting have also expanded upon traditional exponential and logistic models. For example, [20] used the Pearl-Verhulst logistic growth model and implemented the model in MATLAB using numerical solvers such as the Runge-Kutta fourth order method (RK4) and two step Adams-Bashforth method (AB). Their findings suggested that RK4 was an excellent approach to nonlinear differential equation solution, as it was able to mediate environmental constraints and growth rates. [21] showed the precision with which the RK4 method modeled rural population growth and showed it could be used for nonlinear dynamics too.

In the Malaysian context, [22] analysed annual time-series data using real gross domestic product as a proxy for economic growth and population as a proxy for population growth from 1970 to 2009, finding no causal link between the two. [23] further explored the relationship among population, energy consumption, and economic growth through statistical and time series analysis such as unit root tests, cointegration analysis, and Granger causality, showing that population growth influences energy use, which subsequently drives economic development. [24] demonstrated increasing urbanisation trends using census data from 1970 to 2010, while [25] applied exponential growth methods to project population changes over short-term intervals. [26] similarly relied on exponential growth rates when examining population distribution and change across states and districts. Despite these advances, existing studies have focused on Malaysia at the national level, with no specific application to Kedah. The state is particularly relevant due to its rural demographic patterns, which influence regional development [27], and its persistently high poverty and hardcore poverty rates, making it a critical case for population and development studies [28].

Overall, these studies demonstrate ongoing progress in population modeling across different contexts, including Malaysia. Earlier works primarily relied on exponential and logistic growth models [13], [14], [15] and this pattern is also reflected in Malaysian studies, where exponential models were used for short-term population projection [25] and descriptive growth analysis [26]. More recent research has expanded to numerical approaches capable of handling nonlinear population dynamics [20], [21], as well as regression-based modeling, which is gaining attention for its flexibility. Logistic growth remains relevant, particularly through the use of carrying capacity parameters [16], [29], while studies in Nigeria [17] and Tanzania [8] show that exponential models still perform well when data are stable and well managed. In Malaysia, population studies have largely focused on national trends ([22], [23]) and demographic changes linked to urbanisation [24], with limited emphasis on state-level modeling. Despite these methodological advances, no population model has been developed specifically for Kedah, even though it is a demographically significant state marked by rural mobility and persistent poverty ([27], [28]). This highlights a clear research gap. Therefore, this study aims to model population growth in Kedah from 1970 to 2060 using polynomial regression, exponential modeling, and the numerical method known as Runge-Kutta fourth order (RK4) to compare the efficiency and suitability of each approach.

2 MATERIAL AND METHODS

This study utilizes three different mathematical methods: the exponential model, third-order polynomial regression, and the Runge–Kutta fourth order (RK4) method, to observe and predict the population growth for Kedah. Historical demographic data from 1970 to 2024 was used to calibrate the polynomial regression model, while the exponential model and RK4 method were used to forecast population data. Then, the RK4 is projected from 1970 to 2060 in comparison to the official projections from the Department of Statistics Malaysia (DOSM) [4].

2.1 Exponential Growth Model

The exponential growth model, also known as the Malthusian growth model, assumes that the rate of population change is proportional to the current population size, $P(t)$ where t is the time period:

$$\frac{dP}{dt} = aP. \tag{1}$$

The analytical solution is:

$$P(t) = P_0 e^{at}$$

where P_0 is the initial population and a is the growth rate, such as the following:

$$a = \frac{1}{n} ln\left(\frac{P_{t+n}}{P_t}\right) 100$$

where

a = average annual population growth rate,
P_t = Population at time, t,
P_{t+n} = Population at year, $t+n$,
n = number of the year.

2.2 Polynomial Regression Model

In the polynomial regression model, the coefficients b_1, b_2, …,b_n represent the estimated parameters obtained from fitting the model to the observed population data. Specifically, these coefficients determine the contribution of each corresponding polynomial term (linear, quadratic, cubic, etc.) to the overall model. The general form of the polynomial regression model is:

$$P(t) = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + \cdots + b_\mathrm{n} t^\mathrm{n}$$

where

$P(t)$ is the predicted population at time t,
b_0 is the intercept (initial estimated population),
$b_1, b_2, \dots, b_\mathrm{n}$ are the polynomial coefficients,
n is the degree of the polynomial.

The coefficients were computed using the least squares estimation method, which minimizes the sum of squared errors between the observed data and the model predictions. This was carried out using MATLAB, which automatically solves the normal equations to obtain the optimal coefficient values for the best-fitting polynomial curve.

2.3 Numerical Solution using RK4

The Runge–Kutta fourth order (RK4) method numerically solves the growth through mathematical equation known as Ordinary Differential Equations (ODE) as in equation (1) where the approximate solution of the population can be written as follows:

$$P_{n+1} = P_\mathrm{n} + \frac{h}{6}(k_1 + 2k_2 + 2k_3 + k_4)$$

where

$k_1 = f(t_\mathrm{n}, P_\mathrm{n})$,

$k_2 = f\left(t_n + \frac{h}{2}, P_n + \frac{h}{2}k_1\right),$

$k_3 = f\left(t_n + \frac{h}{2}, P_n + \frac{h}{2}k_2\right),$

$k_4 = f(t_n + h, P_n + hk_3).$

The parameter h represents a constant step size. Since the population data is given in annual intervals (as reported by DOSM), we set $h = 1$, meaning the population is estimated each year.

For the initial condition, when $n = 0$, the value P_0 corresponds to the population of Kedah in the base year 1970. This value is taken directly from the DOSM data [4], where the recorded population for Kedah in 1970 was 989,500. Thus, the initial condition for the RK4 numerical solver is $P_0 =$ 989,500 at $t = 1970$. This starting value is then used iteratively with a fixed step size $h = 1$ to compute subsequent population estimates using the RK4 method.

2.4 Model Evaluation

Model accuracy is evaluated using the coefficient of determination (R^2):

$$R^2 = 1 - \frac{\Sigma\left(P_{actual} - P_{predicted}\right)^2}{\Sigma\left(P_{actual} - mean(P_{actual})\right)^2}.$$

An R^2 close to 1 indicates a strong fit between predicted and actual data.

3 RESULTS AND DISCUSSION

Table 1 presents the population data from 1970 to 2024, comparing the results obtained using the exponential, polynomial, and RK4 methods with the actual population figures sourced from DOSM [4].

Table 1: Numerical results comparing the three mathematical methods with the actual population (1970 – 2024)

Year	Actual	Exponential	Polynomial	RK4	Year	Actual	Exponential	Polynomial	RK4
1970	989500	1014185	998111	989500	1998	1601200	1602809	1560798	1602923
1971	1003900	1016080	1014178	1000831	1999	1636500	1634144	1585919	1633508
1972	1017300	1020033	1030502	1012768	2000	1671900	1665431	1611448	1664032
1973	1029000	1025971	1047087	1025329	2001	1703900	1696598	1637384	1694473
1974	1041100	1033855	1063942	1038534	2002	1734800	1727567	1663737	1724803
1975	1054900	1043579	1081067	1052402	2003	1763700	1758260	1690518	1754998
1976	1065400	1055063	1098466	1066958	2004	1792400	1788606	1717727	1785032
1977	1079800	1068255	1116147	1082222	2005	1820300	1818531	1745372	1814879
1978	1090900	1083069	1134113	1098221	2006	1847500	1847947	1773468	1844511
1979	1103400	1099415	1152366	1114981	2007	1874200	1876791	1802013	1873904
1980	1119900	1117236	1170914	1132528	2008	1900200	1904988	1831014	1903029

1981	1140200	1136456	1189761	1150891	2009	1925300	1932447	1860488	1931860
1982	1161800	1156984	1208910	1170102	2010	1949300	1959107	1890434	1960370
1983	1183900	1178753	1228368	1190193	2011	1971800	1984893	1920859	1988533
1984	1206100	1201698	1248141	1211198	2012	2001100	2009716	1951778	2016320
1985	1230800	1225724	1268230	1233152	2013	2039800	2033509	1983194	2043707
1986	1256200	1250761	1288640	1256095	2014	2062700	2056202	2015113	2070665
1987	1281100	1276748	1309384	1280065	2015	2096500	2077709	2047547	2094812
1988	1305400	1303591	1330459	1305106	2016	2119700	2097952	2080506	2107080
1989	1328800	1331216	1351871	1331262	2017	2143900	2116871	2113991	2119653
1990	1352200	1359563	1373633	1358951	2018	2163000	2134380	2148015	2132536
1991	1371300	1388540	1395742	1389168	2019	2173700	2150392	2182592	2145734
1992	1402100	1418074	1418205	1419509	2020	2131400	2164854	2217721	2159252
1993	1434100	1448097	1441034	1449951	2021	2151700	2177686	2253413	2173094
1994	1466600	1478527	1464229	1480474	2022	2163100	2188784	2289687	2187265
1995	1500200	1509287	1487795	1511056	2023	2189300	2198107	2326540	2201772
1996	1533200	1540305	1511742	1541674	2024	2217500	2205580	2363982	2216619
1997	1566900	1571505	1536076	1572304	**R-square value**		0.99903279	0.9811345	0.99921329

Table 2: Comparison of RK4 population projections with DOSM projections (2025-2060)

Year	DOSM Projection	RK4 Projection	Year	DOSM Projection	RK4 Projection
2025	2242800	2231812	2043	2569800	2571788
2026	2268100	2247356	2044	2577900	2594840
2027	2293200	2263258	2045	2585000	2618387
2028	2317800	2279524	2046	2591100	2642439
2029	2342000	2296159	2047	2596200	2667006
2030	2365400	2313171	2048	2600300	2692097
2031	2387900	2330565	2049	2603400	2717724
2032	2409500	2348349	2050	2605400	2743897
2033	2429800	2366529	2051	2606600	2770627
2034	2449100	2385113	2052	2606800	2797926
2035	2467200	2404107	2053	2606300	2825805
2036	2484100	2423520	2054	2604900	2854277
2037	2499900	2443358	2055	2602700	2883352
2038	2514200	2463630	2056	2599600	2913045
2039	2527500	2484344	2057	2595700	2943368
2040	2539600	2505509	2058	2590700	2974334
2041	2550700	2527131	2059	2584900	3005957
2042	2560700	2549222	2060	2578000	3038250

Table 2 compares population projections by DOSM and those generated using the Runge-Kutta fourth order (RK4) numerical method from the year 2025 to 2060. Overall, from 2025 to 2042, the RK4 model predicts slightly lower values than DOSM, indicating a marginally slower growth trend. Between 2043 and 2060, the RK4 estimates begin to diverge upward, showing a progressively larger gap by 2060.

According to Table 1, the R-square values for the RK4, exponential, and polynomial models are 0.99921329, 0.9811345, and 0.99903279, respectively. The R-square (R^2) statistic measures the proportion of variance in the actual population data that can be explained by the model. An R^2 value closer to 1 indicates a stronger fit and higher predictive accuracy. In this case, the RK4 model demonstrates the highest R^2 value, meaning it explains approximately 99.92% of the variation in the observed data indicates the best performance among the three methods. The polynomial model also performs well, with an R^2 of 99.90%, indicating strong alignment with the actual data. In contrast, the exponential model, while still reasonably accurate, explains only 98.11% of the variance, making it less precise in capturing population growth patterns over time. These results suggest that the RK4 method is the most reliable model for population forecasting in this study, followed closely by the polynomial model, consistent with observations in [17] that higher R^2 values reflect stronger model significance and predictive confidence.

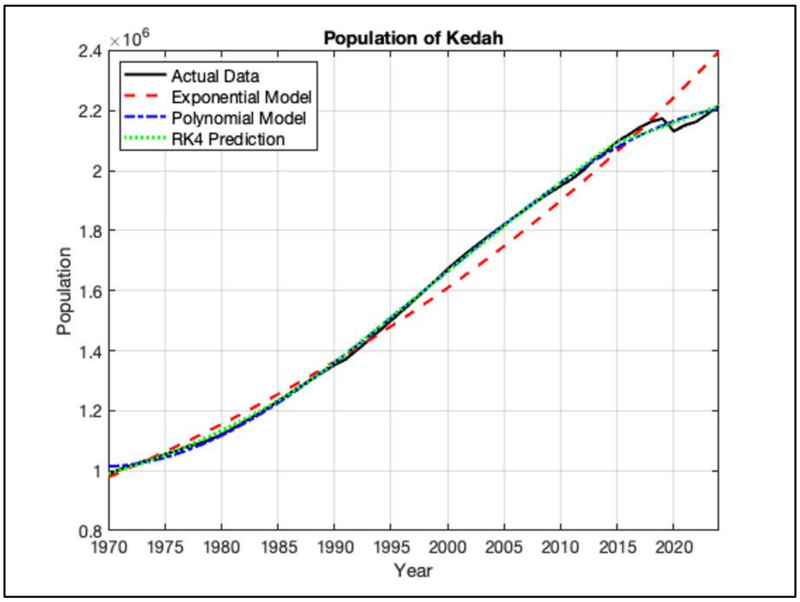

Figure 2: Population of Kedah (1970 – 2024) for actual data compared with the polynomial, exponential, and RK4 methods

Figure 2 illustrates the population trends in Kedah from 1970 to 2024 as modeled by the exponential, polynomial, and RK4 methods, alongside the actual data from DOSM. These plotted values correspond directly to the numerical comparisons presented in Table 1. Although the RK4 curve appears to almost overlap with the actual population trajectory, this is consistent with its high R-square value (0.9992), indicating an excellent model fit. The polynomial model also demonstrates strong agreement with the observed data, whereas the exponential model shows a slight divergence from the actual values.

The outcomes of this study reveal the performance of implementing various modeling techniques to project the population dynamics in Kedah. The R-squared value of 0.99921329 based on the RK4 method indicates that it is superior to the two other methods which are polynomial regression and exponential model in terms of accuracy. This indicates that RK4 was able to predict the population dynamics for both the short and long terms because it essentially fit the actual population estimates from 1970 to 2024 nearly perfectly. When the projections were extended to 2060, the RK4 method predicted continued population growth beyond 2043, while the DOSM projection showed a flattening trend after that year. The disparities between these findings suggest that RK4 may be driven by historical growth momentum, without recognizing any other moderating effects, such as declining fertility levels, population structure age, migration patterns, or economic realignment. Consequently, although RK4 offered the highest accuracy measure for short-term forecasts, it must be used cautiously when considering long-term extrapolations without the inclusion of other demographic variables.

4 CONCLUSION

This study illustrates the use of mathematical techniques to estimate and predict population growth, which is essential for planning and decision-making. The population of Kedah from 1970 to 2024 was modeled and compared using Runge-Kutta fourth order (RK4), third order polynomial regression, and an exponential model. With an R-squared value of 0.99921329, the RK4 approach is the most accurate model for forecasting Kedah's population growth. Furthermore, we provide predictions for the future population in Kedah from 2025 to 2060 and compare them with those given by DOSM. The RK4 model provides a good basis for estimating population fluctuations in Kedah for the reference of policy or decision makers. To improve the accuracy of forecasts for better decision-making in the future, it would be more realistic to include additional variables such as fertility, inwards and outwards migration trends, and economic indicators. In conclusion, this study suggests the importance of numerical and mathematical modeling to comprehend and forecast population trends. Future work should focus on hybrid models that provide high accuracy while also considering the sociodemographic parameters such as age, gender, education level, socioeconomic status, occupation, and geographical location.

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