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COMPARISON OF NEWTON RAPHSON AND SECANT METHODS TO DETERMINE THE OPTIMAL POINT OF TIKTOK APPLICATION

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Abstract:

The growth of digital application users generally follows a non-linear pattern that can be modeled using the logistics growth function, which has the characteristic of an inflection point, which is a condition when the growth rate reaches the maximum value. Optimal point determination involves solving non-linear equations that cannot always be solved directly, so a numerical approach is required. This study aims to determine the optimal growth point of TikTok application users and compare the performance of the Newton–Raphson and Secant methods in solving non-linear equations in the logistics model. User growth data was obtained from the Google Play Store and simulated using logistics growth parameters that represent the characteristics of applications with a high level of virality, with analytics solutions as an evaluation reference. The calculation results show that the optimal point of growth of TikTok users is around the 6th week. The Secant method yielded an optimal point estimate of 5.972 with an RMSE value of 0.0150 and a relative error of 0.25%, while the Newton–Raphson method yielded an estimate of 5.773 with an RMSE value of 0.2140 and a relative error of 3.57%. The difference in error rate and convergence stability shows that the Secant method provides a more effective approach in determining the optimal growth point of digital application users based on the logistics model.

1. Introduction

The rapid development of digital applications makes user growth a key indicator in assessing the sustainability and success of an application. Distribution platforms such as the Google Play Store host millions of apps with a very high level of competition, so only apps that are able to sustain user growth in a sustainable manner can survive in the market (Umer et al., 2021). The phenomenon of user growth in digital applications generally follows the S-curve pattern, which is characterized by the initial phase of slow growth, followed by a significant acceleration, and finally experiencing a slowdown due to market limitations or user saturation (Andika, 2024). This pattern is also seen in popular social media apps such as TikTok, which experienced a surge in user adoption in a certain virality phase before heading into a saturated state (Rosiana et al., 2023).

In the context of these dynamics, the determination of the optimal growth point (inflection point) is very important because it represents the conditions when the user's growth rate is at its maximum. This information has strategic implications in determining the timing of promotion, monetization, and the development of digital application features (Rahayu, 2025; Lu et al., 2023). Mathematically, the optimal point of growth in the logistics model is obtained through the completion of non-linear equations that cannot be determined directly from the raw data. Iterative numerical

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methods such as Newton–Raphson and Secant became relevant to use. The Newton–Raphson method is known to have a fast convergence rate, but requires explicit derivatives of functions, while the Secant method offers flexibility because it does not require derivatives and is still able to produce precise solutions (Sunandar & Indrianto, 2020; Badr et). Therefore, the iterative numerical approach has proven to be effective in solving non-linear problems in various applied fields (Damayanti et al., 2025).

A number of previous studies have made extensive use of statistical and machine learning approaches in analyzing the performance of digital applications (Aryan et al., 2025). Although effective for prediction and classification purposes, such approaches generally do not explicitly determine the optimal point of growth derived from the non-linear nature of logistics growth models (Nurmadhani & Faisol, 2022). Based on the research gap, this study aims to apply the logistics growth model in determining the optimal growth point of TikTok application users as a case study, as well as comparing the performance of the Newton-Raphson method and the Secant method in solving these non-linear problems. The novelty of this research lies in the integration of classical numerical analysis with the context of the growth of data-based digital application users, so that it is expected to make theoretical contributions in the field of numerical analysis as well as practical contributions for digital application developers (Azure, 2023).

2. Literature Review

2.1. Optimal Points in Digital System Optimization

An optimal point is the extreme value of a function used in the optimization process to improve system efficiency. In digital applications, the determination of optimal points is important because it affects the performance and stability of the service. A study by (Khaerunnisa et al., 2025) shows that optimization techniques are able to improve the efficiency of data processing, confirming the important role of this approach in modern systems.

$$t* = \frac{In\,(a)}{r} \tag{1}$$

$t*$ = the time of the optimal user growth point (inflection point),
in (a) = the natural logarithm of the initial constant that reflects the ratio of the initial state of maximum capacity,
r = intrinsic growth rate of users.

2.2. Logistics Growth

User growth in digital applications is generally not linear, but follows a non-linear pattern known as the S-curve. The logistics growth model is widely used to describe this phenomenon because it is able to represent three main phases, namely the initial phase with slow growth, the growth acceleration phase, and the slowdown phase towards a saturated condition or maximum market capacity (Nurmadhani & Faisol, 2024). This model has been widely applied in a variety of contexts, including population growth, technology adoption, as well as the development of social media users. In general, the logistics model is expressed by the equation:

$$P(t) = \frac{K}{1 + Ae^{-rt}} \tag{2}$$

Description:
P(t) = The number of population or application users at the time of the$t$.
t = Time variable (e.g. day, week, month).
K = Maximum capacity.
a = Constant.
r = Intrinsic growth rate.

2.3. The Newton-Raphson Method

The Newton–Raphson method is an iterative numerical method used to find the root of non-linear equations with a fast convergence rate. This method works by utilizing the first derivative of a function to correct the root estimate on each iteration (Badr et al., 2021). However, this method has limitations because it requires calculations of function derivatives that are not always easy to obtain, as well as sensitivity to the selection of initial guesses (Chen et al., 2021).

$$t_{n+1} = t_n - \frac{f(t_n)}{f'(t_n)} \tag{3}$$

Description :
t_n = Approximate root value (optimal point) at the nth iteration.
t_{n+1} = New estimates after correction of Newton's formula.
$f(t)$ = Non-linear functions derived from the logistics model.
$f^i(t)$ = Derivative of $)f(t$

2.4. Secant Method

The Secant method is a development of the Newton–Raphson method that does not require an explicit derivative of a function. This method uses two initial guesses to form a secant line as an approach to the function gradient (Ginantra et al., 2021). Although the convergence rate of the Secant method is generally slower than that of Newton–Raphson, various studies have shown that it is still able to produce accurate solutions with a relatively small number of iterations.

$$t_{n+1} = t_n - f(tn)\frac{tn - tn{-}1}{f(tn) - f(tn{-}1)} \tag{4}$$

Description :
t_{n-1} = Approximate root in previous iteration.
t_n = Approximate current root.
t_{n+1} = New root value after the Secant iteration update.

2.5. RMSE

Root Mean Square Error (RMSE) is a statistical parameter used to measure the error rate between the results of numerical calculations and analytical solutions. RMSE shows the magnitude of the average deviation between the values obtained from the numerical method and the reference value, i.e. the analytical solution, taking into account all observation points used in the analysis. The RMSE measures the magnitude of the average deviation between the calculated value and the reference value by considering the square of the difference, making it more sensitive to large errors (Azure, 2023). Mathematically, RMSE is formulated as:

$$\boldsymbol{RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (t_i^{num} - t_i^{anal})^2}} \tag{5}$$

Description:
$\boldsymbol{t_i^{num}}$ = Value of numerical method results
$\boldsymbol{t_i^{anal}}$ = Reference value of analytics solutions
$\boldsymbol{n}$ = Number of observations

2.6. Relative Error

Relative error is used to measure the degree of deviation from the results of numerical calculations against analytical solutions in the form of percentages. This parameter gives an idea of how much of a difference there is between the numerically obtained values compared to the reference values, i.e. the analytical solution, at each observation point. Mathematically, relative error is formulated as:

$$\boldsymbol{Error\ Relatif = \left|\frac{t_i^{num} - t_i^{anal}}{t_i^{anal}}\right| \times 100\%} \tag{6}$$

Remarks
$\boldsymbol{t_i^{num}}$= Value of the numerical method result
$\boldsymbol{t_i^{anal}}$ = Reference value of the analytics solution

3. Research Methods

This study uses a quantitative approach with a combination of mathematical and computational analysis. This research went through stages to evaluate the growth pattern of Tiktok application users through a logistics model and determine the optimal growth point using the Newton–Raphson and Secant numerical methods. The diagram is presented in Figure 3.1.

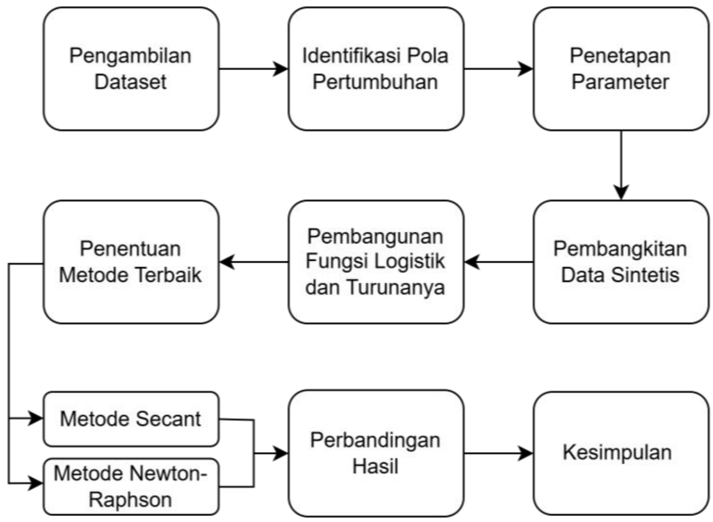

Figure 3.1 Flowchart

The flowchart illustrates the steps of this research, starting from the extraction of raw application data to processing it into a growth simulation. The core process is to compare the two methods (Newton-Raphson and Secant) in finding the optimal point, to determine which method is the fastest and most accurate.

3.1. Dataset Retrieval

This study did not use the app population in general, but this study determined a specific object (saturated sample) in the form of TikTok application data extracted from the Google Play Store dataset available in the Kaggle public repository (2024). The selection of TikTok as a single sample was based on the criteria of "apps with high virality characteristics" that have massive download counts and a rapid growth rate, making them very representative to test using a logistics growth model. The data captured included the application name attributes, total installations, and other supporting parameters used to calibrate the simulation model.

3.1.1. Parameter Setting

The determination of parameters in the logistics growth model was carried out to represent the growth characteristics of TikTok application users realistically and measurably in Table 3.1.

Table 3.1 Parameters

Parameters	Value	Remarks
K	500.000.000	Maximum Capacity
P(0)	100.000	Number of Early Users

a	49	Initial constant
r	0.65	Growth rate

3.1.2. Data Types and Data Sources

Secondary data was obtained from the Google Play Store Apps dataset on Kaggle (2024), with a specific focus on the TikTok app. The key variables extracted include the Number of Installations (as the basis for estimating the capacity parameter K). Given the static cumulative nature of the data, this study synthesized the data to form a quasi-time-series. This approach allows growth patterns to be mathematically modeled even without direct historical data, according to computational research standards.

3.2. Synthetic Data Development of User Growth

Because the secondary dataset from the Google Play Store does not present a history of user additions in a time-series, this study reconstructs TikTok user growth data through a simulation approach. Data is generated following the Logistics Distribution Function pattern, the most accurate model for describing the virality phase to application saturation. The logistics model is used to describe the dynamics of application user growth in the early phase until it is close to the saturation point. Based on the parameters that have been set, synthetic data on the number of users in the period of 0 to 10 weeks is obtained.

Table 3.2 Growth Data

Week (t)	User (P(t))
0	10,000
1	16,835
2	27,849
3	45,702
4	73,804
5	116,983
6	180,337
7	270,723
8	360,204
9	428,152
10	461,842

Table 3.2 shows the number of users increasing significantly from week 0 to week 10. The fastest growth occurs in the 3rd to 7th week, after the 8th week, the increase in the number of users starts to slow down. This trend confirms the S-curve pattern in logistics models, that applications enter a period of accelerated growth before moving towards saturation.

3.3. The Newton-Raphson Method

The Newton–Raphson method as one of the numerical approaches to determine the optimal point of growth. This method works iteratively by utilizing the function slope information to gradually improve the approach value. In this study, the Newton–Raphson method is applied by giving one initial guess value, then iterating until a convergent value is obtained. This method was chosen because it is known to have a high convergence speed in delicate functions

3.4. Secant Method

The Secant method is used as a comparison method against Newton–Raphson. In contrast to Newton–Raphson, the Secant method does not require the inforomation of derivative functions, but instead uses two initial approach values to form a cut-off line as an estimate of the direction of convergence. In this study, the Secant method was applied to evaluate whether a no-derivatives approach can result in better accuracy and efficiency in determining the optimal point of growth of application users.

3.5. Model Evaluation

Model evaluation was carried out to assess the level of accuracy and efficiency of the two numerical methods in determining the optimal point of growth of application users. The evaluation was carried out by comparing the numerical results of each method to the analytical solution used as a reference value. One of the calculations used is Root Mean Square Error (RMSE), RMSE is used to evaluate the degree of proximity of Newton–Raphson and Secant methods to optimal growth point analytical solutions. Smaller RMSE values indicate that the method produces more accurate and stable estimates. In addition to RMSE, the relative error in this study aims to provide a more intuitive evaluation of the performance of the Newton–Raphson and Secant methods. The low relative error value indicates that the method has a high level of precision in determining the optimal growth point of digital application users.

4. Results and Discussion

4.1. Determination of Optimal Points

Analytical optimal point determination, optimal point is obtained by calculating equation (1), calculation using a program based on Figure 4.1.

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••• Titik optimal (t*): 5.987
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Figure 4.1 Calculation of the Optimal Point

Based on Figure 4.1 The result is 5,987 ≈ 6 Sunday . So that from Results the Application achieve acceleration Growth highest on Around Sunday 6th. Value this digunakan sebagai acuan untuk mengevaluasi hasil yang diperoleh melalui metode Newton–Raphson dan Secant.

4.2. Results of the Newton-Raphson Method

The Newton–Raphson method is used because it has a rapid convergence on functions whose first derivatives are known. The calculation process begins with the selection of one initial guess value, namely =4. The selection of this initial guess was based on the results of observation of user growth data which showed a significant acceleration before week 6. t_0

TABEL ITERASI METODE NEWTON-RAPHSON

Iterasi	t_n	f(t_n)	f'(t_n)	t_(n+1)
1	4.000	-3.068	4.693	4.654
2	4.653	-1.810	2.927	5.271
3	5.272	-0.598	1.823	5.600
4	5.600	-0.161	1.309	5.723
5	5.723	-0.043	1.160	5.760
6	5.760	-0.011	1.110	5.770
7	5.770	-0.003	1.096	5.773

Figure 4.2 Newton-Raphson iterations

Based on Figure 4.2, the results of the calculation of the Newton-Raphson method iteration are presented in Table 4.1.

Table 4.1 Newton-Raphson iteration

Iteration	t_n	$f(t_n)$	$f'(t_n)$	t_{n+1}
1	4.000	-3.068	4.693	4.653
2	4.653	-1.810	2.927	5.272
3	5.272	-0.598	1.823	5.600
4	5.600	-0.161	1.309	5.723
5	5.723	-0.043	1.160	5.760
6	5.760	-0.011	1.110	5.770
7	5.770	-0.003	1.096	5.773

Newton-Raphson results: $t *_{NR} = 5.773 \approx 5.8$
Newton–Raphson Method achieve Convergence in 7 iteration , with Results 5.773 Around 5.8 Sunday , Results the Close Up nilai titik optimal (≈6 minggu).

4.3. Secant Method Results

The Secant method was chosen because it does not require function derivatives, making it more flexible to use on complex functions. In contrast to Newton–Raphson, the Secant method begins with two initial guesses, namely = 4 and =7. These two guesses were chosen to flank the analytics solution which is around week 6, so it is expected to speed up the convergence process.$t_0 t_1$

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TABEL ITERASI METODE SECANT
------------------------------------------------------------
Iterasi | t_(n-1) | t_n     | f(t_(n-1)) | f(t_n)  | t_(n+1)
------------------------------------------------------------
1       |   4.000 |   7.000 |     -3.068 |   0.538 |   6.552
2       |   7.000 |   5.539 |      0.538 |  -0.317 |   6.081
3       |   5.539 |   5.883 |     -0.317 |  -0.031 |   5.920
4       |   5.883 |   5.944 |     -0.031 |  -0.007 |   5.962
5       |   5.944 |   5.962 |     -0.007 |  -0.002 |   5.969
6       |   5.962 |   5.967 |     -0.002 |  -0.001 |   5.972
```

Figure 4.3 Secant Iteration

Based on the calculation of the iteration of the secant method shown by Figure 4.3, the calculation results are presented in Table 4.2.

Table 4.2 Secant Iteration

Iteration	t_{n-1}	t_n	$f(t_{n-1})$	$f(t_n)$	t_{n+1}
1	4.0	7.0	-3.068	0.538	5.539
2	7.0	5.539	0.538	-0.317	5.883
3	5.539	5.883	-0.317	-0.031	5.944
4	5.883	5.944	-0.031	-0.007	5.962

5	5.944	5.962	-0.007	-0.002	5.969
6	5.962	5.967	-0,002	-0.001	5.972

Secant Results: $t *_{SC} = 5.972 \approx 6$
The Secant method provides results that are very close to the analytical solution, which is 5.972 or about 6 weeks, with a total of 6 iterations. This method is slightly slower than Newton-Raphson but more flexible because it does not require derivative information of functions.

4.4. Comparison of Method Results

After obtaining the results of the Newton-Raphson method and also the secant method. We can compare the two methods.

Table 4.3 Comparison of Methods

Method	Optimal Point	Iteration
Newton-Raphson	5.773	7
Secant	5.972	6

Based on Table 4.3 shows that Both numerical methods produce estimates that are very close to the analytical value. Newton–Raphson provides the fastest convergence, while Secant excels in flexibility. Both results reinforce the validity of the logistics model used to describe the growth of application users.

4.5. Model Evaluation Results

Before drawing conclusions about the effectiveness of the Newton–Raphson and Secant methods in determining the optimal point of growth of application users, it is necessary to evaluate the model on the performance of the two methods.

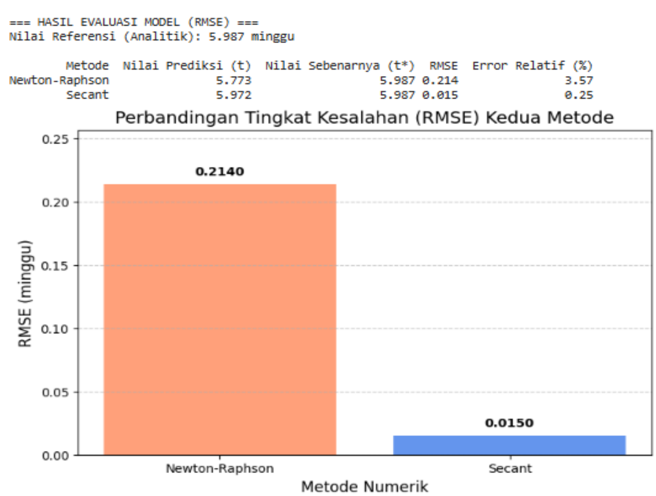

Figure 4.4 Model Evaluation and RMSE Comparison

Based on Figure 4.4 of the model evaluation results, there is a significant difference between the Newton-Raphson and Secant methods. And the results of the evaluation score can be clearly presented through Table 4.4.

Table 4.4 Model Evaluation Results

Method	Method Results	Analytical Analysis	RMSE	Relative Error (%)
Secant	5.972	5.987	0.0150	0.25
Newton-Raphson	5.773	5.987	0.2140	3.57

Based on Table 4.4 of the comparison of the two numerical methods, it can be seen that Newton-Raphson and Secant are able to produce an estimate of the optimal point of user growth that is very close to the analytical value, which is about 6 weeks. However, the degree of proximity of each method is different. The Secant method produces the smallest relative error of **0.25%,** thus providing an estimate that is almost identical to that of an analytical solution. Meanwhile, the Newton–Raphson method obtained a relative error **of 3.57%,** indicating a deviation that was slightly larger than the actual value.

This difference indicates that, in the case of the logistics function used, the Secant method is superior in terms of accuracy even though it does not utilize function derivatives. In contrast, Newton–Raphson still shows stable convergence performance, but is sensitive to the selection of initial values resulting in higher errors.

5. Conclusion

Based on the simulation carried out on the logistics model using the parameters of the TikTok application, the conclusion drawn by this particular study is that the momentum of user growth attained the optimal point within the range of the 6th week (analysis: 5,987). In finding the optimal point, it was found that the Secant Method is superior to the Newton-Raphson method, both in terms of accuracy and efficiency. In other words, the Secant method is capable of reaching the exact solution (t: 5.972) within only 6 cycles with an extremely low level of error percentage (RMSE = 0.0150), while the Newton-Raphson method results in higher deviations (RMSE = 0.2140) with an increased number of cycles. This shows that the no-derivatives approach to Secant is more effective for the particular characteristics of the growth function.

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