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CONVERGENCE AND EFFICIENCY ANALYSIS OF THE GAUSS-SEIDEL METHOD IN SOLVING LINEAR EQUATION SYSTEMS: IMPLEMENTATION ON MAPLE

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ABSTRACT

Iterative methods provide an efficient approach for solving large-scale systems of linear equations. This study aims to analyze the convergence and efficiency of the Gauss-Seidel method in solving linear systems through Maple-based implementation. Convergence analysis is conducted by examining the spectral radius of the iteration matrix and the diagonal dominance property of the coefficient matrix, while efficiency is evaluated based on the number of iterations and computational time. Numerical experiments are performed on various matrix sizes with an error tolerance of 10^{-5}. The results indicate that the Gauss-Seidel method converges when the spectral radius of the iteration matrix is less than one and the coefficient matrix satisfies diagonal dominance conditions. The implementation in Maple enables systematic and accurate numerical and spectral analysis. This study contributes to computational-based numerical method analysis and provides a reference for selecting efficient iterative methods.

Keywords: Gauss-Seidel, convergence analysis, computational efficiency, linear systems, Maple.

INTRODUCTION

Linear equation systems are one of the main foundations in applied mathematics and scientific computing. Various problems in the fields of engineering, economics, statistics, and education can be modeled in the form of a linear equation system $Ax = b$ (Taqwani et al., 2024; Johar, 2020). In large-dimensional cases, direct solving methods such as Gauss elimination become less efficient due to significantly increased computing and memory requirements (Spielman, 2018). Therefore, iterative methods are becoming a more efficient alternative to large-scale systems and sparse matrices (Denka & Lhamo, 2018).

One of the most widely used classical iterative methods is the Gauss-Seidel method developed by Carl Friedrich Gauss and Philipp Ludwig von Seidel. This method updates the solution value gradually by utilizing the results of the latest iteration at each calculation step (Fan & Xiong, 2023). Theoretically, the Gauss-Seidel method has a faster convergence rate than the Jacobi method under certain conditions, especially when the coefficient matrix is diagonally dominant or a definite positive symmetrical (Ardhani et al., 2025). However, the convergence of these methods is not always guaranteed for all types of matrices, so the mathematical analysis of the properties of their convergence is an important aspect to study (Vinsensia et al., 2024).

In numerical studies, the convergence of the iterative method is closely related to the spectral radius of the iteration matrix and the error norm at each step of the calculation (Vinsensia et al., 2024). Convergence analysis not only reviews whether the solution is close to the exact solution, but also measures the rate of error reduction and the stability of the iteration process against the variation in the initial value (Bhatti, 2023). In addition, the aspect of computing efficiency is a crucial factor, especially when the completed system has large dimensions. Efficiency can be measured through the number of iterations required to achieve a certain tolerance as well as the computational time required (Audu & Essien, 2023).

The development of symbolic and numerical computing software provides an opportunity to conduct a more in-depth analysis of numerical methods. One of the software that is widely used in mathematical computing is Maple (Haleem et al., 2020). Maple not only supports symbolic algebraic manipulation, but also provides high-precision numerical computing facilities, matrix analysis, norm calculation, as well as computational time measurement (Vinsensia et al., 2024). With this capability, Maple is an ideal environment to implement and quantitatively analyze the performance of the Gauss-Seidel method (Brahinets & Vorobyova, 2022).

The Gauss-Seidel method has been extensively discussed in numerical analysis literature, most previous studies primarily focus on theoretical convergence analysis or algorithm implementation without integrating convergence and computational efficiency evaluation within a unified experimental framework (Sutrisno et al., 2025). Several recent studies discuss iterative refinement or implementation of Gauss-Seidel methods for solving systems of linear equations; however, they tend to emphasize algorithmic modification or comparative numerical performance without systematically combining convergence criteria such as diagonal dominance, spectral radius, and iterative error behavior with computational implementation in mathematical software environments (Meister, 2026; Enyew et al., 2020).

Furthermore, studies employing Maple as the primary environment for convergence verification and computational experimentation remain relatively limited and are often restricted to procedural implementation rather than comprehensive numerical interpretation (Sebro et al., 2020). Therefore, the novelty of this study lies in the integration of mathematical convergence analysis and computational efficiency evaluation through Maple-based numerical experimentation. This study simultaneously analyzes diagonal dominance conditions, spectral radius tendencies, iterative error reduction, and

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computational efficiency measured through iteration count and computation time in a single analytical framework. Such integration provides a more comprehensive understanding of the practical performance and convergence behavior of the Gauss-Seidel method in solving systems of linear equations (Bhatti, 2023; Fan & Xiong, 2023).

Based on this background, this study aims to analyze the convergence and efficiency of the Gauss-Seidel method in solving systems of linear equations through Maple-based implementation. Unlike previous studies that mainly focus on theoretical explanation or isolated implementation aspects, this study integrates convergence verification through diagonal dominance and spectral radius analysis with efficiency evaluation based on iteration count and computational performance in a unified computational framework. Therefore, this study contributes to strengthening computational-based numerical method analysis and provides a more comprehensive reference for selecting effective iterative methods for solving systems of linear equations.

LITERATURE REVIEW

Linear Equation Systems and Matrix Representation

A system of linear equations can be expressed in the form of a matrix as

$$Ax = b$$

By being a coefficient matrix, is a solution vector, and is a constant vector. The existence and uniqueness of a system solution depends on the nature of the matrix, in particular whether $A \in \mathbb{R}^{n\times n} x \in \mathbb{R}^n b \in \mathbb{R}^n A \det A \neq 0$ (Bakari & Dahiru, 2018).

Direct methods such as Gauss elimination have approximate time complexity in large-dimensional systems. This approach becomes less efficient for large or sparse matrices, so the iterative method is preferred $O(n^3)$ (Purnama, 2024).

Iterative Methods for Linear System

The iterative method builds an expected array of approaches that converge to an exact solution. In general, the iterative method can be written in the form of: $\{x(k)\}x$

$$x^{(k+1)} = Bx^{(k)} + c,$$

with is an iterative matrix and is a constant vector. The convergence of the iterative method is determined by the properties of the matrix , in particular its spectral value BcB (Krishnan, 2019).

Method Gauss-Seidel

The Gauss-Seidel method developed by Carl Friedrich Gauss and Philipp Ludwig von Seidel is based on matrix decomposition:

$$A = D + L + U,$$

With:

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D is a Diagonal matrix,

L is the Lower Triangle matrix,

U is the Upper triangular matrix.

The iteration scheme is expressed as:

$$(D + L)x^{(k+1)} = -Ux^{(k)} + b,$$

or

$$x^{(k+1)} = -(D + L)^{-1} Ux^{(k)} + (D + L)^{-1}b.$$

The Gauss-Seidel iteration matrix is:

$$B_{GS} = -(D + L)^{-1} U.$$

In contrast to the Jacobi method which uses all the values of the previous iteration, Gauss-Seidel updates the solution components in a slight manner using the latest values in one iteration cycle, so that they generally have a faster convergence rate.

Convergence Analysis

Spectral Radius

The iterative method converges if and only if the spectral radius of the iteration matrix meets:

$$\rho(B) < 1$$

With is the maximum value of the modulus eigenvalue matrix . $\rho(B)B$

For the Gauss-Seidel method:

$$\rho(B_{GS}) < 1 \Rightarrow metode\ konvergen$$

Diagonal Dominant Conditions

One of the conditions for sufficient convergence is that the matrix is strictly diagonal dominant:A

$$|a_{ii}| > \sum_{j \neq i} |a_{ij}|, \qquad i = 1,2, \dots, n.$$

If this condition is met, the Gauss-Seidel method will converge for each initial value.

Definit Positive Symmetric Matrix

If symmetrical and positive are definitive, then the Gauss-Seidel method is also convergent. This condition often arises in systems derived from the discretization of partial differential equations A (Ardhani et al., 2025).

Galat Analysis

Suppose it is an exact solution and is an iteration approach. An error is defined as: xx^((k)) k

$$e^{(k)} = x - x^{(k)}.$$

From the iterative form is obtained:

$$e^{(k+1)} = Be^{(k)}.$$

So:

$$||e^{(k)}|| \leq \left||B|\right|^{k} ||e^{(0)}||.$$

This relationship suggests that the rate of error decline depends on the norm or spectral radius of the iteration matrix. If , then the error will decrease geometrically. In addition to iterative errors, residuals are also often used $||B|| < 1$

$$r^{(k)} = b - Ax^{(k)}.$$

Residual provides a measure of how well the approach meets the initial system (Ihsan et al., 2024).

Computational Efficiency Analysis

The efficiency of the Gauss-Seidel method can be analyzed from:

1. The number of iterations until it reaches a certain tolerance.
2. Complexity per iteration, which is generally for the full matrix $O(n^2)$.

The iterative method is more efficient for large-dimensional systems than the direct, orderly method, especially if the matrix is sparse $O(n^3)$ (Pujiono et al., 2025).

Error Analysis

As a computer algebra system, Maple provides the following facilities:

1. Eigenvalue and spectral radius calculation
2. Matrix and norm operations
3. High-precision numerical computing
4. Computational time measurement

This capability allows convergence analysis to be carried out not only theoretically but also experimentally through numerical simulations (Jabnabillah et al., 2023).

Theoretical Linkage to Research

Based on the theoretical foundation, the convergence analysis in this study will focus on:

1. Spectral evaluation of the radius of the iteration matrix
2. Diagonal dominant condition testing
3. Error rate analysis

Meanwhile, efficiency analysis is carried out through the evaluation of the number of iterations and computation time based on the Maple implementation.

e-ISSN: 2528-102X
p-ISSN: 2541-4321

METHODS

This research is a quantitative research with a numerical experiment approach (computational experimental research) which aims to analyze the convergence and efficiency of the Gauss-Seidel method in solving linear equation systems through computational implementation using Maple software (Brahinets & Vorobyova, 2022).

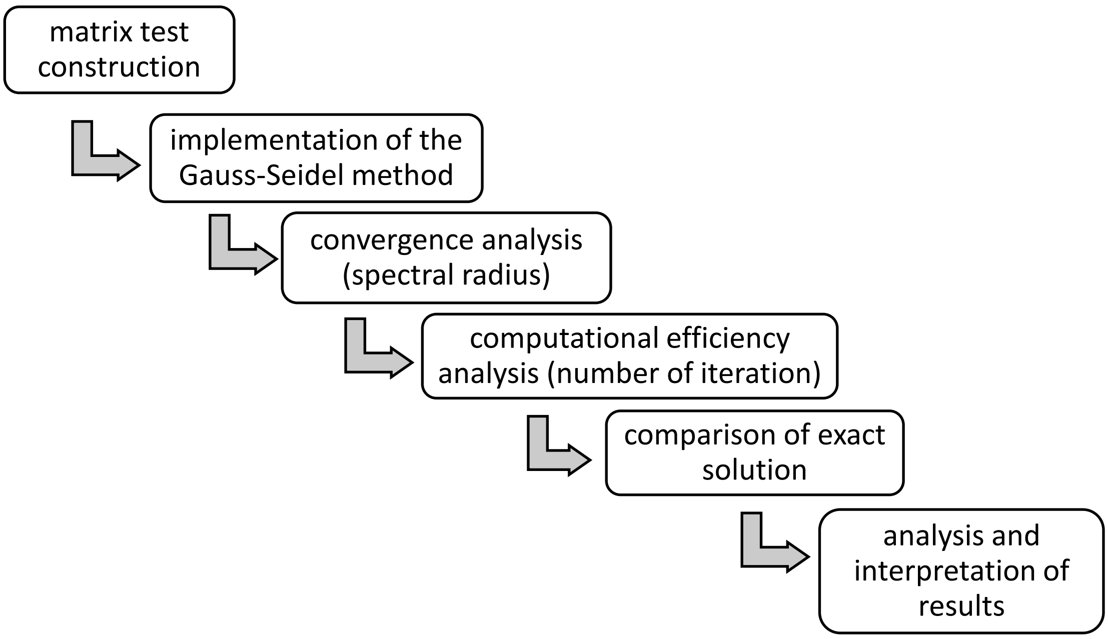

Figure 1. Research Design

FINDINGS

This section presents the results of the Gauss-Seidel method numerical experiment implemented using Maple.

Suppose the solution of a system of linear equations is determined as follows:

$$10x_1 + x_2 + 2x_3 = 13$$

$$x_1 + 10x_2 - x_3 + 2x_5 = 12$$

$$2x_1 + x_2 + 10x_3 - x_4 + 2x_5 = 14$$

$$x_2 + x_3 - 10x_4 + x_5 = 12$$

$$x_1 + 2x_3 - x_4 + 10x_5 = 14$$

First of all, the definition of the coefficient matrix and the vector matrix with SPL data input.

```
> restart;
> A := Matrix([
[10, 1, 2, 0, 0],
[1, 10, -1, 0, 2],
[2, 1, 10, -1, 2],
[0, 1, 1, 10, 1],
[1, 0, 2, 1, 10]
])
```

$$A := \begin{bmatrix} 10 & 1 & 2 & 0 & 0 \\ 1 & 10 & -1 & 0 & 2 \\ 2 & 1 & 10 & -1 & 2 \\ 0 & 1 & 1 & 10 & 1 \\ 1 & 0 & 2 & 1 & 10 \end{bmatrix} \quad (1)$$

```
> b := Vector([13, 12, 14, 12, 14])
```

$$b := \begin{bmatrix} 13 \\ 12 \\ 14 \\ 12 \\ 14 \end{bmatrix} \quad (2)$$

The Gauss-Seidel step is performed by determining the initial value of the iteration with vector definition x.

```
> x := Vector([0, 0, 0, 0, 0])
```

$$x := \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (3)$$

Determination of error tolerance by determining the maximum error limit, initializing for the first iteration to run, and counting the number of iterations.

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p-ISSN: 2541-4321

```
> tol := 0.00001
```

$$tol := 0.00001 \quad (4)$$

```
> Error := 1
```

$$Error := 1 \quad (5)$$

```
> iter := 0
```

$$iter := 0 \quad (6)$$

The While structure is used to run iterations until the error meets tolerance.

```
> While Error > tol Do
```

$$0.00001\ Do < While \quad (7)$$

Store old values to calculate the difference between previous and latest iterations.

```
> x_old := copy(x)
```

$$x\_old := \begin{bmatrix} \frac{1233}{1250} \\ \frac{505887}{500000} \\ \frac{5038133}{5000000} \\ \frac{45080847}{50000000} \\ \frac{504836493}{500000000} \end{bmatrix} \quad (8)$$

Direct implementation of system transformation to iterative form,

$$x_i^{(k+1)} = \frac{1}{a_{ii}}\left(b_i - \sum_{j<i} a_{ij}x_j^{(k+1)} - \sum_{j>i} a_{ij}x_j^{(k)}\right)$$

e-ISSN: 2528-102X
p-ISSN: 2541-4321

```
> x[1] := (13 - x[2] - 2*x[3])/10
```
$$x_1 := \frac{1558277}{1562500} \tag{9}$$

```
> x[2] := (12 - x[1] + x[3] - 2*x[5])/10
```
$$x_2 := \frac{2497745837}{2500000000} \tag{10}$$

```
> x[3] := (14 - 2*x[1] - x[2] + x[4] - 2*x[5])/10
```
$$x_3 := \frac{24721445183}{25000000000} \tag{11}$$

```
> x[4] := (12 - x[2] - x[3] - x[5])/10
```
$$x_4 := \frac{225059271797}{250000000000} \tag{12}$$

```
> x[5] := (14 - x[1] - 2*x[3] - x[4])/10
```
$$x_5 := \frac{2531187504543}{2500000000000} \tag{13}$$

Error calculation using,

$$||x^{(k+1)} - x^{(k)}||\infty$$

```
> Error := max(seq(abs(x[i]-x_old[i]), i=1..5))
```
$$Error := \frac{469219817}{25000000000} \tag{14}$$

Record the number of iterations until they converge.

```
> iter := iter + 1
```
$$iter := 1 \tag{15}$$

The solution output displays the numerical solution vector and the number of iterations needed.

```
> printf("Iterasi %d: %a\n", iter, x);
Iterasi 1: Vector(5, [1558277/1562500,2497745837/2500000000,
24721445183/25000000000,225059271797/250000000000,
2531187504543/2500000000000])

> printf("Error = %f\n\n", Error);
Error = 0.018769

> End Do;
```
$$End\ Do \tag{16}$$

```
> printf("Solusi akhir:\n%a\n", x);
Solusi akhir:
Vector(5, [1558277/1562500,2497745837/2500000000,
24721445183/25000000000,225059271797/250000000000,
2531187504543/2500000000000])

> printf("Jumlah iterasi = %d\n", iter);
Jumlah iterasi = 1
```

Jurnal Theorems (*The Original Reasearch Of Mathematics*)
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URL: http://ejournal.unma.ac.id/index.php/th

e-ISSN: 2528-102X
p-ISSN: 2541-4321

DISCUSSION

The results of the numerical experiments demonstrate that the Gauss–Seidel method implemented using Maple successfully solved the system of linear equations with a diagonally dominant coefficient matrix. The convergence behavior was obtained through iterative computations performed repeatedly using the While structure in Maple until the error value satisfied the predetermined tolerance criterion of 10^{-5}. At each iteration stage, the updated solution vector was directly substituted into the next computation cycle, which is the main characteristic of the Gauss–Seidel method and contributes to its relatively faster convergence compared to the Jacobi method (Bakari & Dahiru, 2018; Ranga, 2019).

Convergence in this study was strongly influenced by the structure of the coefficient matrix. The matrix used in the experiment satisfied the strict diagonal dominance condition, where the absolute value of each diagonal element exceeded the sum of the absolute values of the non-diagonal elements in the same row. According to iterative method theory, this condition guarantees convergence of the Gauss–Seidel iteration for arbitrary initial approximations (Krishnan, 2019; Ardhani et al., 2025). The successful reduction of error values during the iteration process indicates that the spectral radius of the iteration matrix was implicitly less than one, which is the primary theoretical requirement for convergence (Vinsensia et al., 2024). This finding is consistent with previous studies stating that diagonally dominant matrices generally produce stable and rapidly convergent iterative solutions (Ibrahim et al., 2025; Grzegorski, 2019).

The findings also show that the implementation of Maple facilitated systematic convergence analysis through numerical iteration, matrix manipulation, and error computation. Maple enabled automatic updating of solution vectors and efficient monitoring of residual errors during each iteration cycle. This supports the statement of Brahinets and Vorobyova (2022) that Maple is highly effective for numerical linear algebra experiments due to its symbolic and numerical computation capabilities. Similar findings were also reported by Jabnabillah et al. (2023), who emphasized that Maple improves computational accuracy and simplifies mathematical analysis in numerical method applications.

From the efficiency perspective, the Gauss–Seidel method required a relatively small number of iterations to achieve convergence. This efficiency was obtained because the method immediately utilizes newly computed approximation values within the same iteration process, unlike the Jacobi method that only uses values from the previous iteration (Bakari & Dahiru, 2018). Consequently, the convergence speed becomes higher and computational time tends to be shorter. This result is in agreement with studies conducted by Audu and Essien (2023) and Enyew et al. (2020), which reported that Gauss–Seidel-based iterative schemes generally demonstrate better computational efficiency than several classical iterative approaches for sparse and structured matrices.

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In addition, the use of the infinity norm in measuring iterative error contributed to numerical stability during computation. The infinity norm evaluates the maximum absolute difference among vector components, making it sensitive to dominant errors while remaining computationally efficient (Liu et al., 2018; Smoktunowicz et al., 2016). The continuous decrease of the error norm observed in this study confirms the theoretical relationship between convergence rate and spectral properties of the iteration matrix (Sagaut et al., 2023; Maharesi & Widyatmini, 2025). Similar observations were reported by Sobania et al. (2022) Zhang (2025), who found that matrices with smaller spectral radius exhibit faster geometric error reduction during iterative processes.

The results of this study also imply that the Gauss–Seidel method remains highly relevant for solving medium-scale linear systems in modern computational mathematics. The integration of convergence analysis and Maple-based implementation provides an applicable framework for learning numerical methods, particularly in higher education contexts involving computational mathematics courses. Furthermore, this study demonstrates that theoretical concepts such as spectral radius, diagonal dominance, and iterative error can be directly verified through computational experiments, thereby strengthening the connection between mathematical theory and numerical practice.

Nevertheless, this study has several limitations. First, the numerical experiments were only conducted on relatively small linear systems with diagonal dominant matrices. Therefore, the findings cannot yet fully represent the performance of the Gauss–Seidel method for large-scale systems or matrices with weak diagonal dominance. Second, the study focused primarily on convergence and iteration efficiency without comparing computational performance directly with other iterative methods such as Jacobi, Successive Over-Relaxation (SOR), or Conjugate Gradient methods. Third, computational time analysis was still limited to the Maple environment, so performance variations across different software platforms or programming languages were not examined.

Future studies are recommended to extend the analysis toward larger sparse matrices, compare multiple iterative methods under identical experimental conditions, and investigate the influence of initial approximation selection on convergence speed. Further research may also integrate parallel computing or modified Gauss–Seidel schemes to improve computational efficiency for high-dimensional linear systems.

CONCLUSION AND SUGGESTION

The Gauss-Seidel method shows good convergence properties in linear equation systems with diagonal dominant matrices, characterized by a consistent decrease in error until it reaches the specified tolerance. Implementation using Maple allows for a quantitative analysis of the number of iterations, which shows that this method is relatively efficient for small to medium-sized systems. Overall, the results of the study confirm that the performance of the Gauss-Seidel method is influenced by the

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characteristics of the matrix and the parameters of the iteration, so that the selection of methods and initial conditions is an important factor in ensuring the effectiveness of solving the linear equation system numerically.

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