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Scope

Our scope extends to interdisciplinary research that combines elements from the aforementioned areas to address complex systems and challenges in information sciences, we strive to foster a holistic understanding and innovative solutions to contemporary IT problems.

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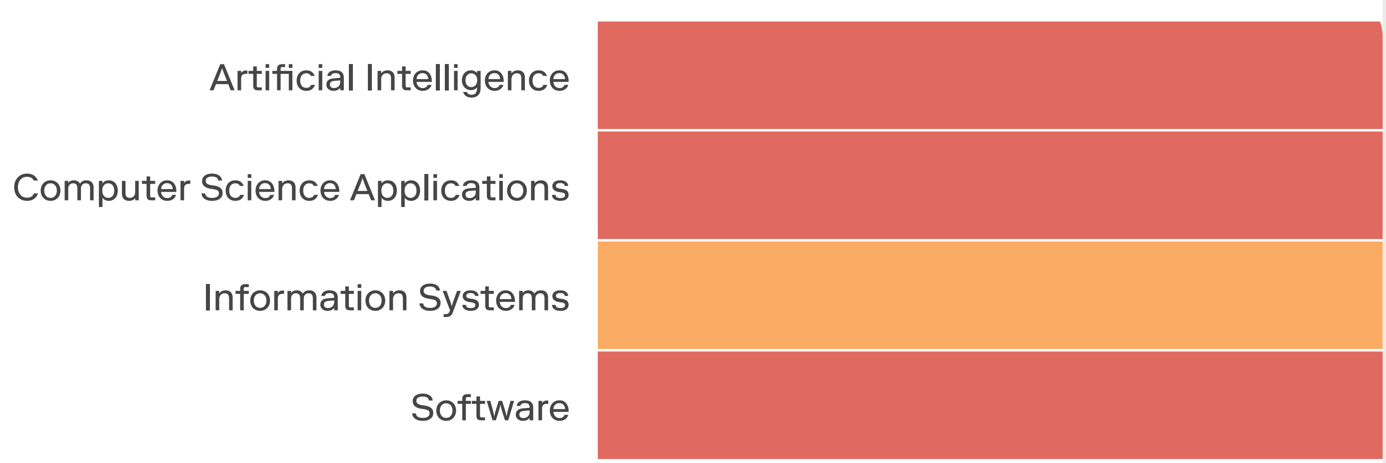

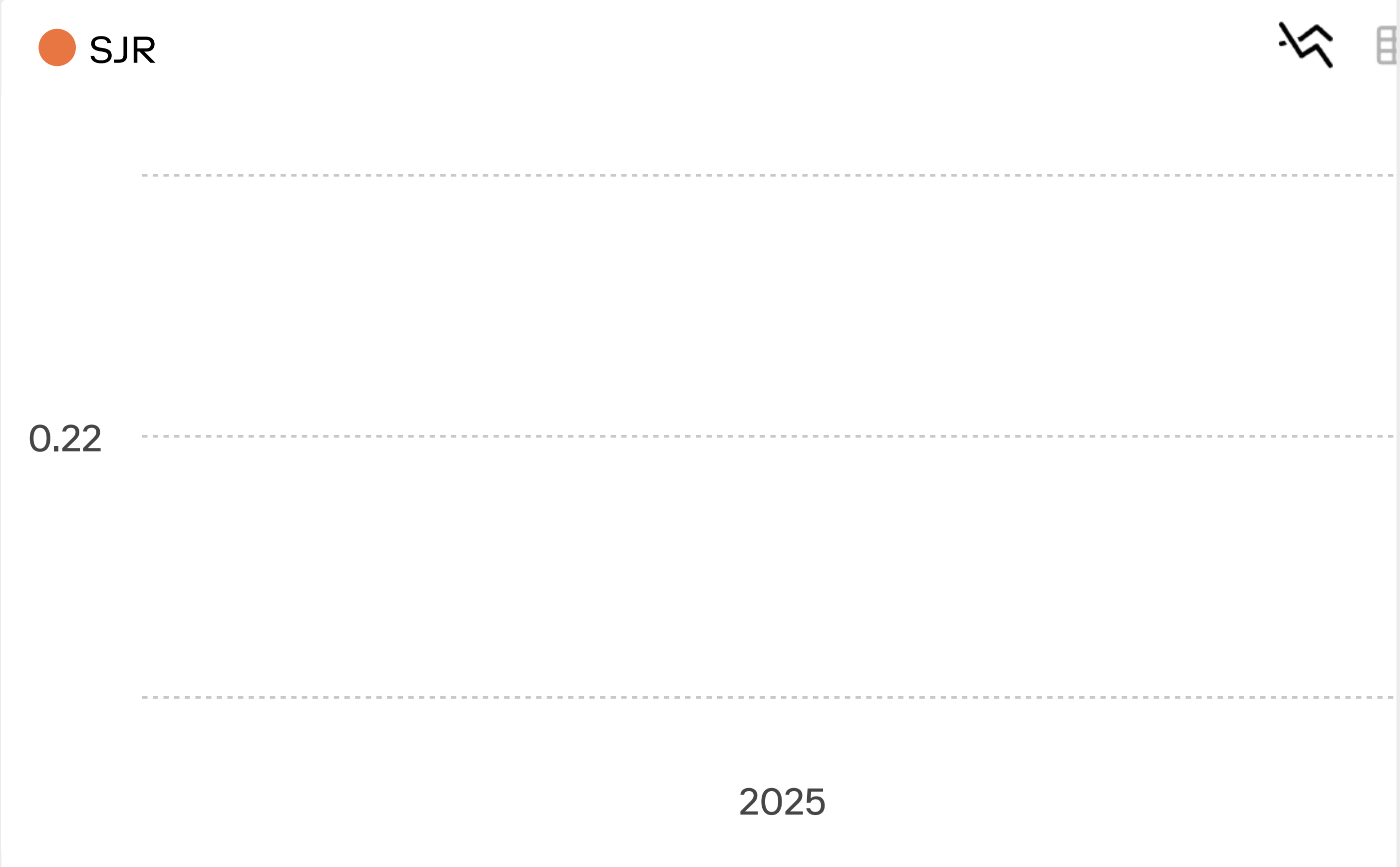
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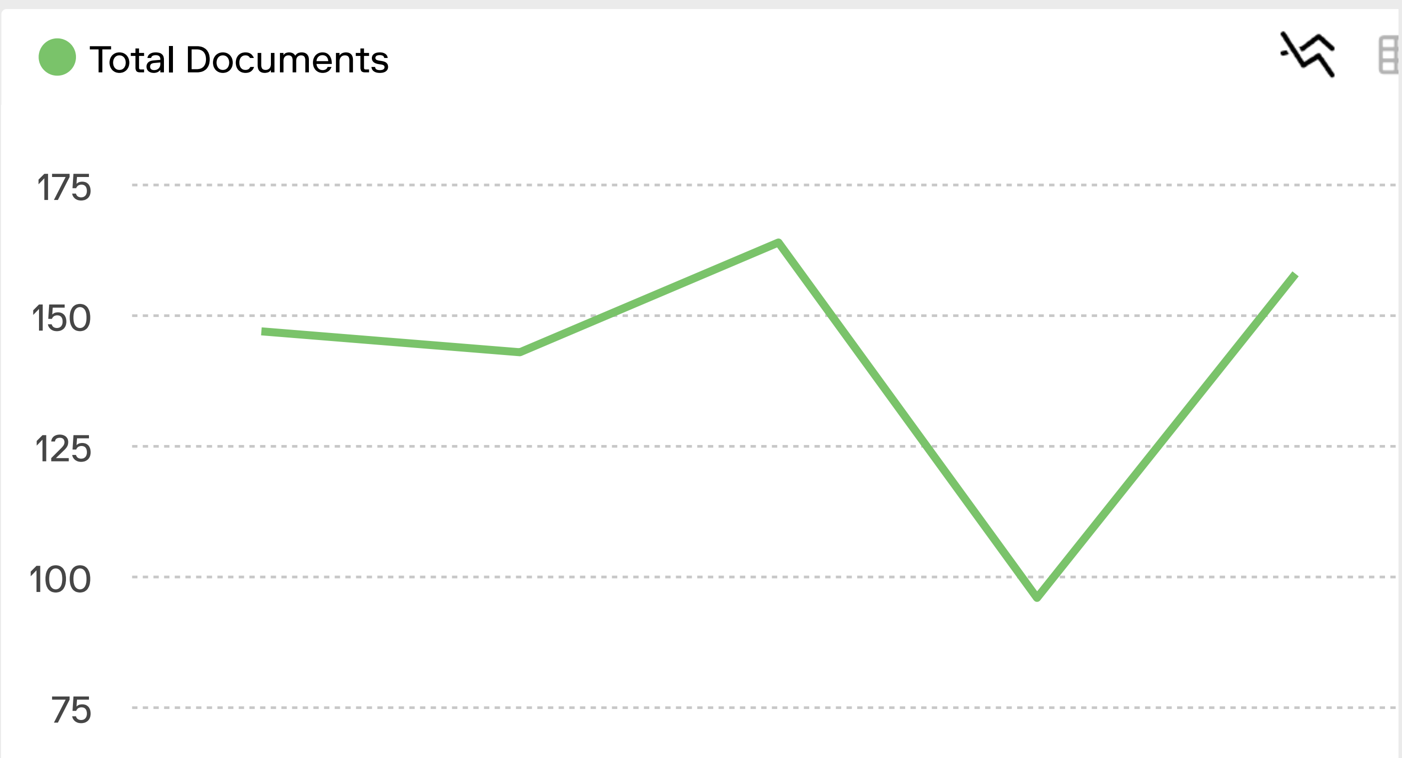
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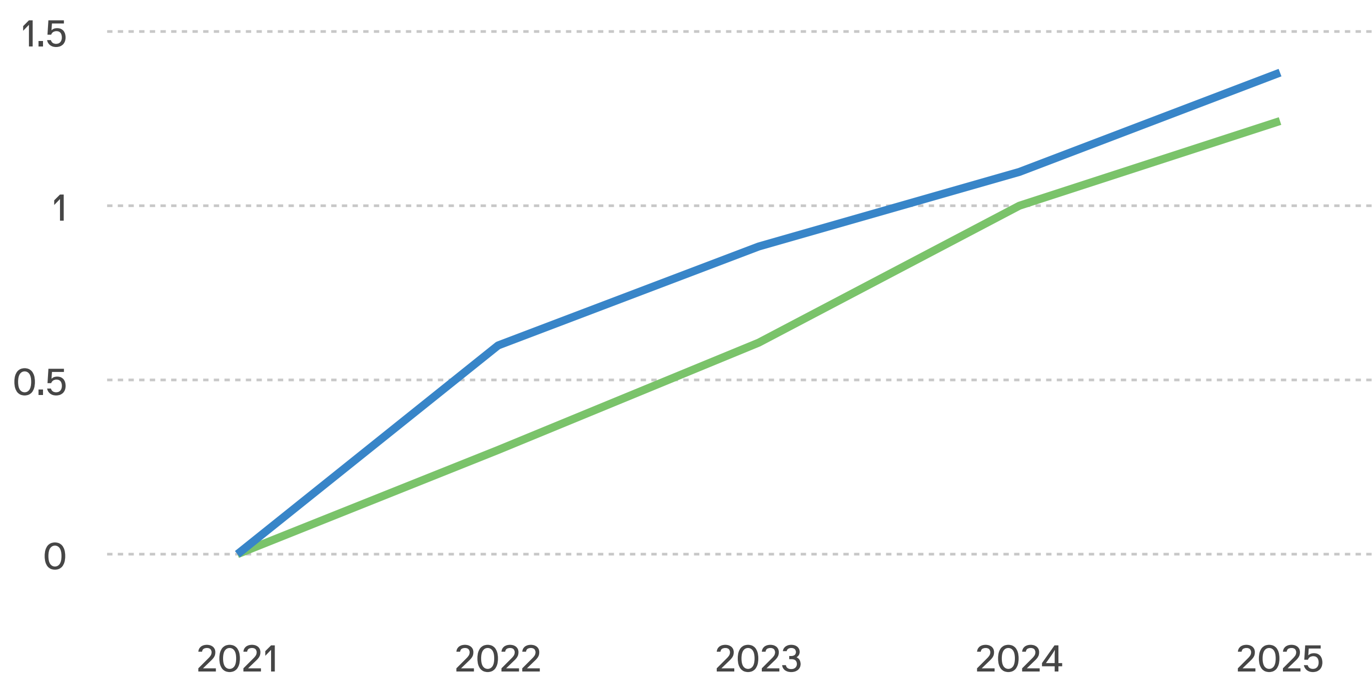
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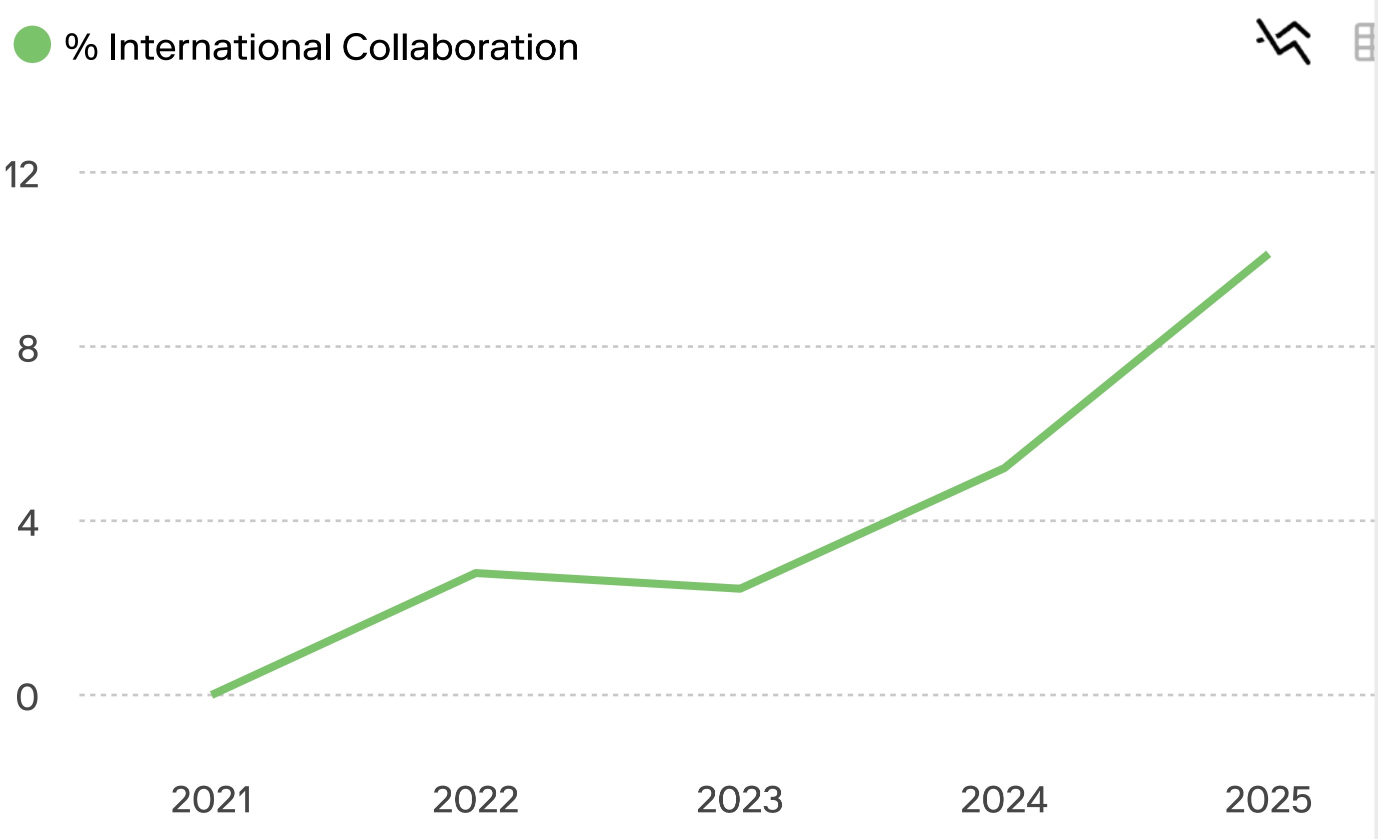
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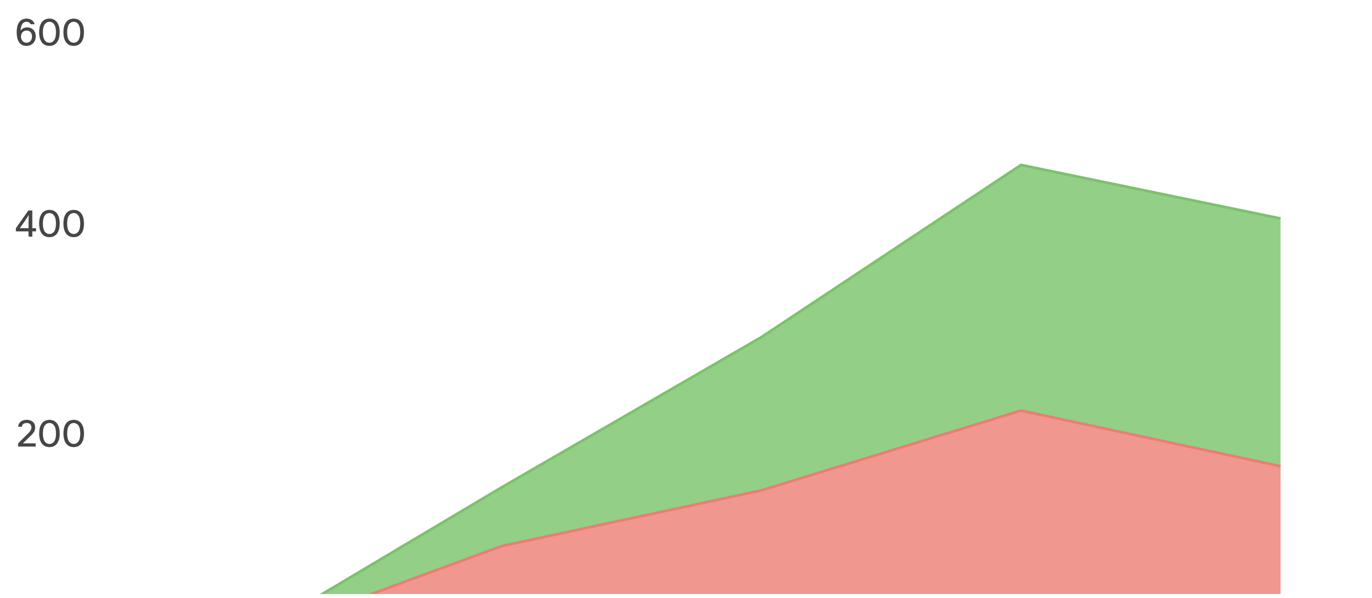

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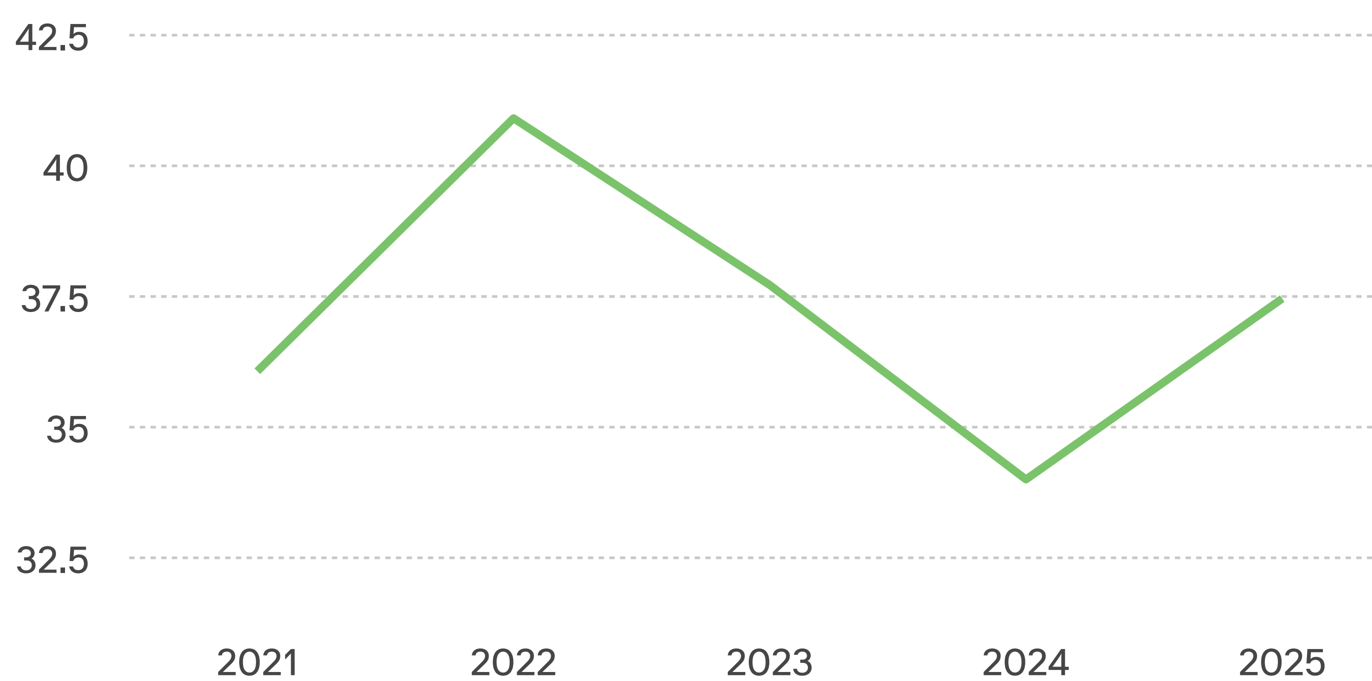

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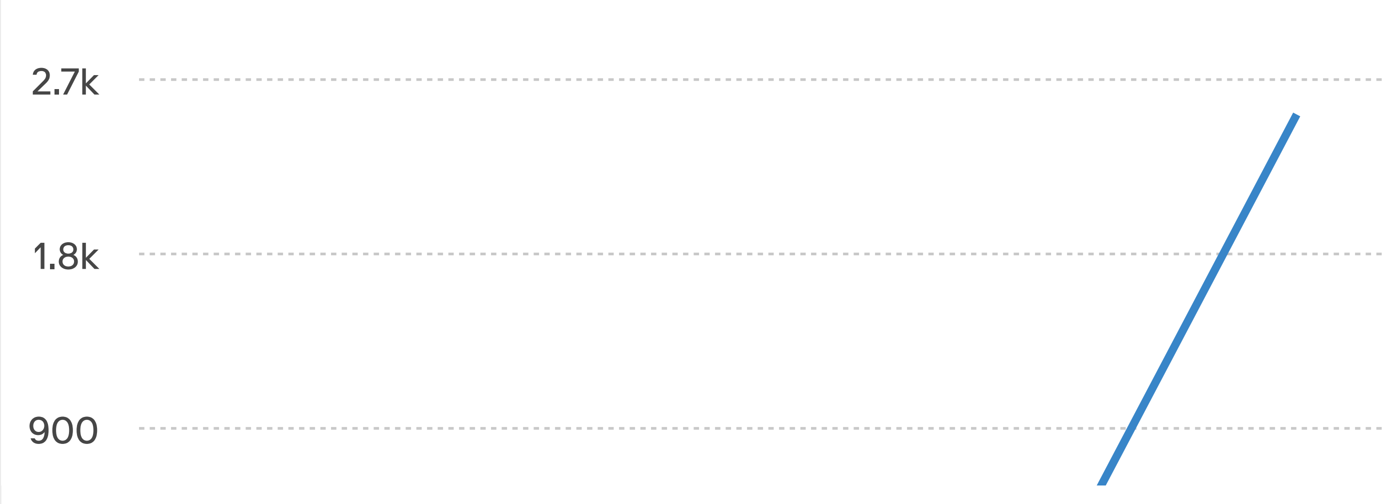
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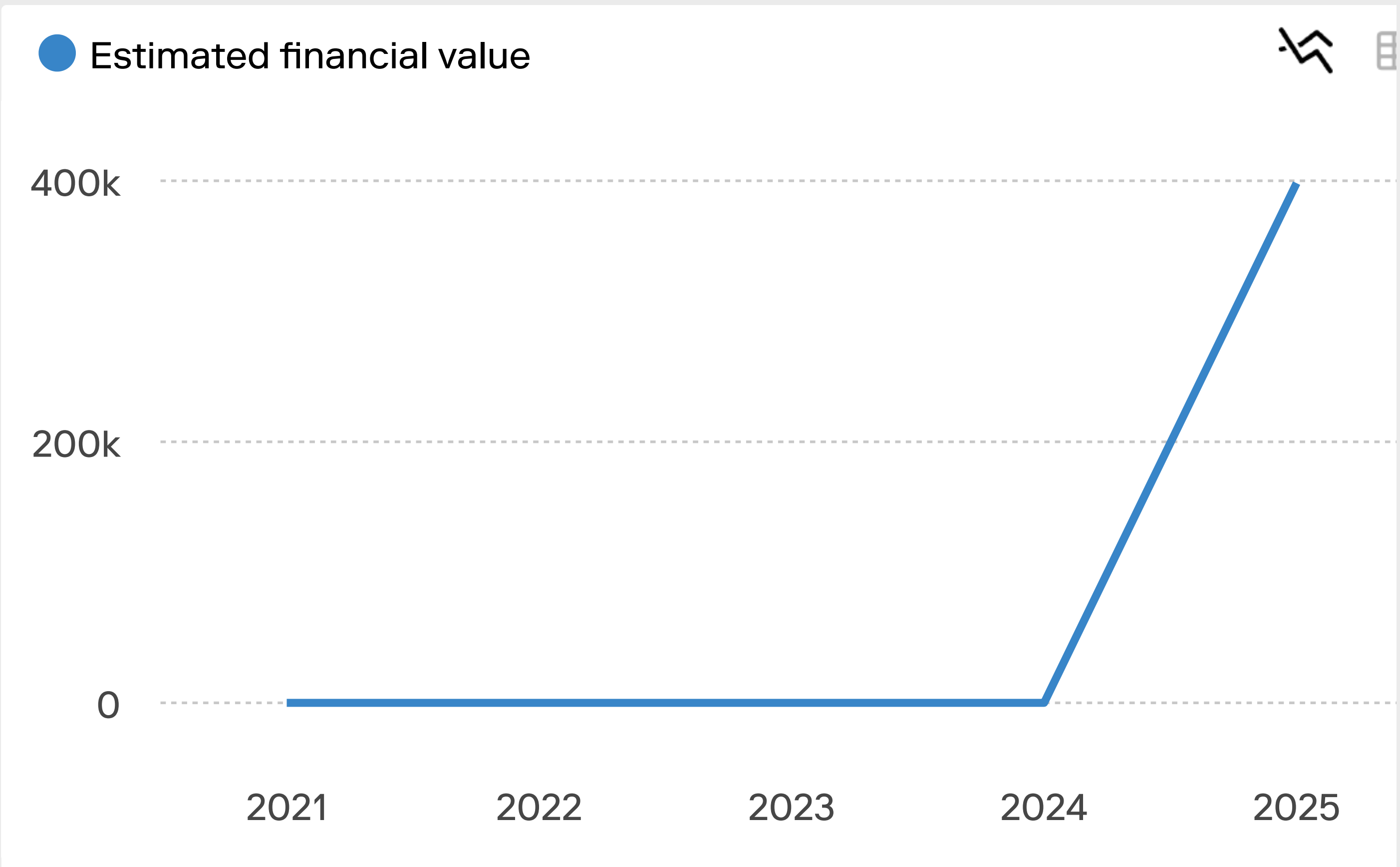
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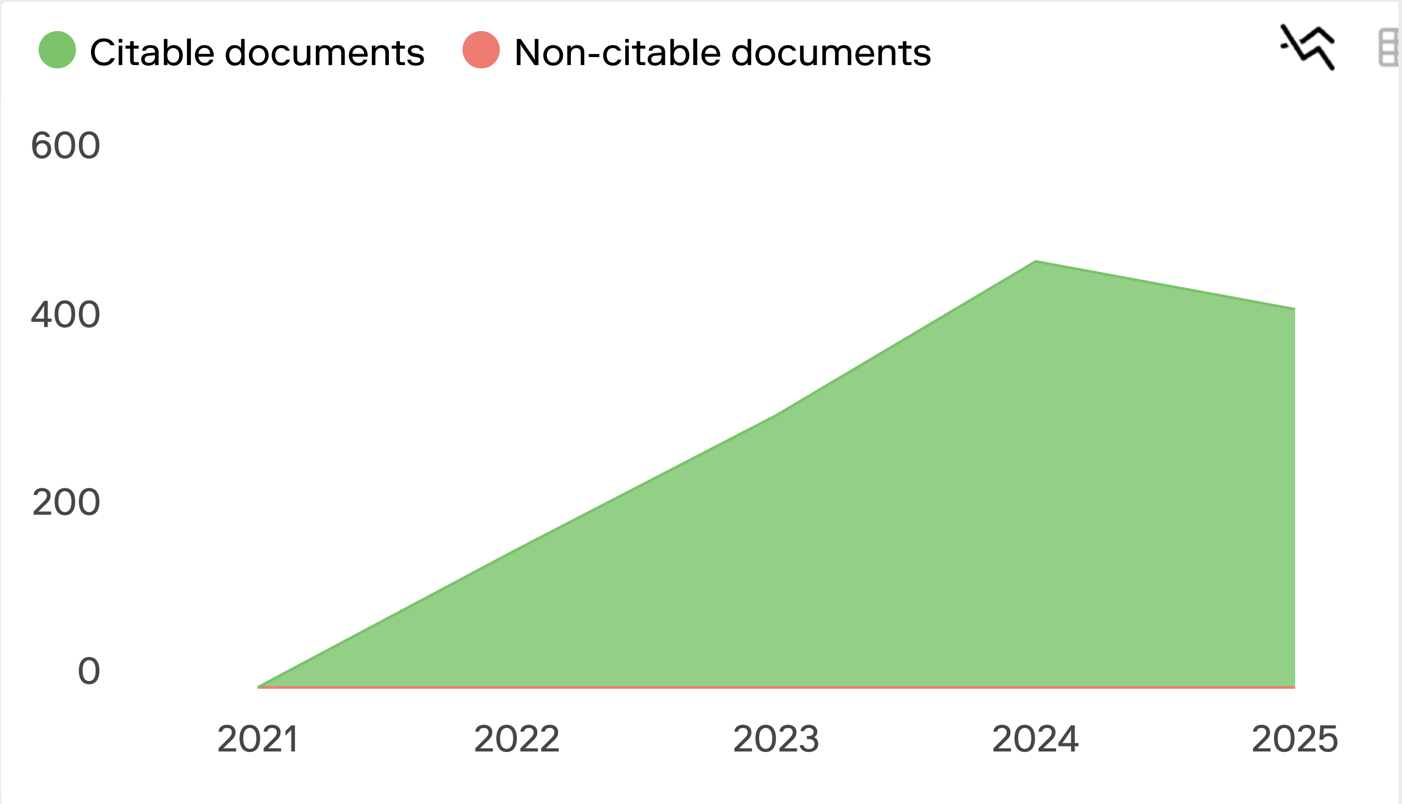
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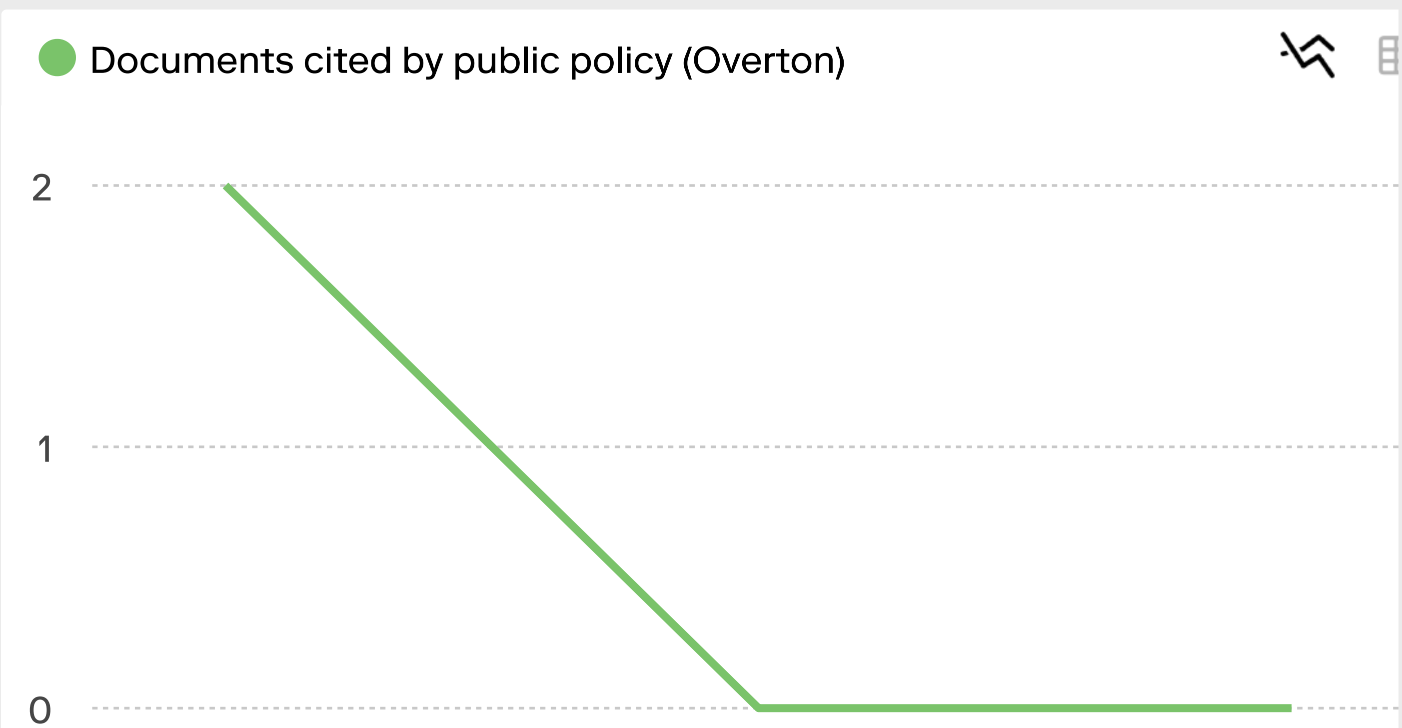
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[RESTI] Editor Decision

2026-01-04 12:41 AM

V Joko Riyono, Aina Latifa Riyana Putri, Fayza Nayla Riyana Putri:

We have reached a decision regarding your submission to Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), "Convergence and Empirical Performance of Tanh-Based Adaptive Particle Swarm Optimization".

Our decision is: Revisions Required

chief
Ikatan Ahli Informatika Indonesia (IAII) Nusantara
jurnal@iaii.or.id

Reviewer A:
Recommendation: Revisions Required

Is the title appropriate and aligned with the journal's scope?

Yes

Does the abstract concisely inform readers and summarize the research?

Yes

Are relevant prior studies adequately contextualized, especially in the background?

Yes

Does the author provide in-depth analysis, particularly in the discussion and results sections?

Yes

Does the author demonstrate sufficient scientific reasoning, argumentation and interpretation?

Yes

Are descriptions and explanations presented clearly and understandably?

Yes

Are figures, tables, and numbers of adequate quality and easy to interpret?

Yes

Are visuals like diagrams and images used appropriately and clearly?

Yes

Does the manuscript present an original contribution?

Yes

Is the writing style suitably academic with clear and proper language?

Yes

Give constructive feedback:

The abstract is somewhat dense, with several long sentences that could be shortened to improve readability. The novelty should be clarified by briefly explaining how the tanh function enhances stability. Including one quantitative performance metric would make the results more convincing. The description of the 30 dimensional performance should be more specific rather than saying it “slightly declines.” The final sentence can also be strengthened by emphasizing the broader impact of the findings.

Consider adding a short paragraph summarizing limitations of existing adaptive PSO methods (TVAC, SCAC, SBAC) to highlight the novelty of TB-PSO more clearly in the introduction.

Some of the figures can be enlarged a bit

The conclusion is good but can be strengthened by adding a brief summary of why tanh-based adaptation works well and clear future directions (e.g., hybrid methods, real world datasets). Consider stating explicitly whether TB-PSO is computationally heavier or comparable to other PSO variants.

[RESTI] Editor Decision

2026-06-01 03:37 PM

Joko Riyono, Aina Latifa Riyana Putri, Fayza Nayla Riyana Putri:

We have reached a decision regarding your submission to Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), "Convergence and Empirical Performance of Tanh-Based Adaptive Particle Swarm Optimization".

Our decision is to: Accept Submission

chief
Ikatan Ahli Informatika Indonesia (IAII) Nusantara
jurnal.resti@gmai.com

Reviewer C:
Recommendation: Accept Submission

Is the title appropriate and aligned with the journal's scope?

Yes

Does the abstract concisely inform readers and summarize the research?

Yes

Are relevant prior studies adequately contextualized, especially in the background?

Yes

Does the author provide in-depth analysis, particularly in the discussion and results sections?

Yes

Does the author demonstrate sufficient scientific reasoning, argumentation and interpretation?

Yes

Are descriptions and explanations presented clearly and understandably?

Yes

Are figures, tables, and numbers of adequate quality and easy to interpret?

Yes

Are visuals like diagrams and images used appropriately and clearly?

Yes

Does the manuscript present an original contribution?

Yes

Is the writing style suitably academic with clear and proper language?

Unsure

Give constructive feedback:

Fix critical inconsistencies/typos in Methods (high priority). The benchmark-function indexing is inconsistent (e.g., Ackley is labeled f6, while later sections describe five functions f1–f5 and mention "six" problems).
Strengthen evidence for "computationally comparable" claim. You state TB-PSO has no significant overhead; consider adding a short runtime table or complexity discussion to make this verifiable.

Reviewer E:
Recommendation: Accept Submission

Is the title appropriate and aligned with the journal's scope?

Yes

Does the abstract concisely inform readers and summarize the research?

Yes

Are relevant prior studies adequately contextualized, especially in the background?

Yes

Does the author provide in-depth analysis, particularly in the discussion and results sections?

Yes

Does the author demonstrate sufficient scientific reasoning, argumentation and interpretation?

Yes

Are descriptions and explanations presented clearly and understandably?

Yes

Are figures, tables, and numbers of adequate quality and easy to interpret?

Yes

Are visuals like diagrams and images used appropriately and clearly?

Yes

Does the manuscript present an original contribution?

Yes

Is the writing style suitably academic with clear and proper language?

Yes

Give constructive feedback:

(1)The manuscript has been revised properly and correctly,
(2) The paper is well-written,
(3) Recommendation Accept Submission

[Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)]

[RESTI] Editor Decision

2026-06-19 05:28 PM

Joko Riyono, Aina Latifa Riyana Putri, Fayza Nayla Riyana Putri:

The editing of your submission, "Convergence and Empirical Performance of Tanh-Based Adaptive Particle Swarm Optimization," is complete. We are now sending it to production.

Submission URL: https://jurnal.iaii.or.id/index.php/RESTI/authorDashboard/submission/7247

chief
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Inbox

J. Riyono <jokoriyono@trisakti.ac.id> Jun 3, 2026, 10:47 AM

to jurnal.resti

Dear Resti Editor,

Please find attached the Letter of Agreement, the final revised manuscript **(with the updated and changes of author information)**, and the proof of payment.

Article ID: ID7247

Thank you for your attention.

Best regards,
Joko Riyono

3 Attachments • Scanned by Gmail

Jurnal Resti Jun 6, 2026, 11:55 PM

to me

Dear Author,

Thank you for submitting your manuscript. However, please carefully review the manuscript to ensure full compliance with the RESTI journal template and formatting guidelines. The following issues require revision:

1. Please follow the journal template carefully when providing author and affiliation information.
2. Figure 1 appears blurry. Please replace it with a clearer, higher-resolution version. In addition, ensure that the figure caption uses a font size of **8 pt**.
3. Please avoid using terms such as *"the following equation"* or *"the following formula."* Instead, refer directly to the equation number. Also, ensure that every equation is properly cited and referred to within the manuscript text.
4. Please avoid the use of numbering formats and bullet points throughout the manuscript.
5. Provide an introductory paragraph before entering any sub-section. For example, Section 3.1 should not appear immediately after Chapter 3 without a preceding introduction.
6. Tables should be presented as tables and should not resemble figures (e.g., Table 2). Please ensure that all tables follow the formatting guidelines specified in the journal template.
7. Ensure that all references comply with the **IEEE citation style**, contain complete bibliographic information, and include **active (clickable) DOI links** where available.

Please check and recheck the manuscript thoroughly before resubmission. When submitting the revised version, kindly explain the revisions made in your reply email. We look forward to receiving your revised manuscript as soon as possible so that it can be processed and published according to schedule.

Thank you for your cooperation.

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--

an ordinary person

J. Riyono <jokoriyono@trisakti.ac.id> Jun 8, 2026, 8:00 AM

to jurnal.resti

Dear Resti Editor,

Please find attached the the final revised manuscript

2 Attachments • Scanned by Gmail

Jurnal Resti Jun 11, 2026, 8:22 PM (11 days ago)

to me

Dear Author,

Thank you for the revision. However, we still identified several issues that require correction:

1. Numbering is still present in the manuscript (see page 4).
2. Please ensure that all equations are properly cited and referred to within the manuscript text.
3. The phrase *"is defined as follows"* is still used. Please revise the wording and cite the equation directly instead.
4. Table 1 is still presented in a figure-like format. In addition, please avoid displaying algorithms or pseudocode. Kindly convert this section into a narrative explanation.
5. Tables 2–4 do not yet follow the journal formatting guidelines. Please revise them according to the template.

Please carefully check and recheck the manuscript thoroughly before resubmitting.

Thank you for your cooperation.

--

an ordinary person

J. Riyono Jun 12, 2026, 11:17 AM (10 days ago)

Dear Editor Resti, here we present the revisions according to the editor team's request. Thank you for your attention. Best regards Joko Riyono.

Jurnal Resti Jun 15, 2026, 9:47 AM (7 days ago)

to me

Could you please provide an explanation of the fixes that have been implemented?

Thank you

J. Riyono <jokoriyono@trisakti.ac.id> Jun 15, 2026, 11:58 AM (7 days ago)

to Jurnal

To Editor Resti
Here we present feedback on our revised manuscript and the final draft.
Thank you.

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Jurnal Resti Jun 15, 2026, 10:38 PM (7 days ago)

to me

Dear Author,

Thank you for the revision. The manuscript has improved significantly.

However, I would like to ask about citations [9] and [10]. Are these citations intentionally placed at the beginning of the sentence? In most cases, citations are typically placed at the end of the relevant sentence or statement.

Please review the placement of these citations and revise them if necessary to ensure consistency with the journal's citation style.

Thank you for your attention to this matter.

Best regards,

J. Riyono <jokoriyono@trisakti.ac.id> Jun 16, 2026, 6:57 AM (6 days ago)

to Jurnal

To the editor of the journal, thank you for your correction. Here are the improvements we have made. Best regards

2 Attachments • Scanned by Gmail

J. Riyono <jokoriyono@trisakti.ac.id> Jun 19, 2026, 3:21 PM (3 days ago)

to Jurnal

With respect, Editor Resti Jurnal.

Thank you for your correction. Here we present the corrections we have made along with the completeness for the next process. Thank you for your attention and cooperation.

Best regards

Joko Riyono

4 Attachments • Scanned by Gmail

Jurnal Resti Jun 20, 2026, 12:09 AM (2 days ago)

to me

Thank you very much.

[RESTI] Editor Decision

External

Inbox

j

chief Sat, Jun 20, 12:28 AM (2 days ago)

to me, Aina, Fayza

Joko Riyono, Aina Latifa Riyana Putri, Fayza Nayla Riyana Putri:

The editing of your submission, "Convergence and Empirical Performance of Tanh-Based Adaptive Particle Swarm Optimization," is complete. We are now sending it to production.

Submission URL: https://jurnal.iaii.or.id/index.php/RESTI/authorDashboard/submission/7247

chief
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jurnal.resti@gmai.com

Jurnal Resti: Request for Final Revision Prior to Publication

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r

rita komalasari Sun, Jun 21, 8:20 PM (22 hours ago)

to ainaqp, me

Dear Ms. Aina Latifa Riyana Putri,

We would like to kindly request that you revise your manuscript before it proceeds to the publication stage.

Please address the following points:

1. Figure 2 still contains labels written in Bahasa Indonesia. Please revise all labels and annotations in the figure to English to ensure consistency with the language of the manuscript.
2. Please ensure that the Turnitin similarity index of the revised manuscript is below 20%. Based on the current Turnitin report, the manuscript has a similarity score of 29%.
3. Kindly provide the email addresses of the following co-authors to complete the publication metadata:
    - Sofia Debi Puspa
    - Supriyadi
    - Christina Eni Pujiastuti

In addition, we noticed that the author name "Fayza Nayla Riyana Putri," which was previously listed in the manuscript metadata, no longer appears in the current version. Please clarify whether this author has been removed and provide the reason for this change.

4. To ensure the best publication quality for your manuscript, we kindly request that you send the original file for Figure 5 in high-definition quality. The current version of the figure does not provide sufficient clarity for publication. Please provide the original image file (JPG, PNG, TIFF, or another suitable format) with a minimum resolution of 300 dpi.

Kindly make the necessary revisions using the attached Word file, as it is the editor-edited version of your manuscript and should be used as the basis for all revisions.

Please submit the revised manuscript, the requested author information, and the high-resolution figure file no later than June 23, 2026, so that it can be processed for publication in Vol. 10 No. 3 (June 2026).

Thank you for your attention and cooperation. We look forward to receiving your revised submission.

Yours sincerely,

Rita Komalasari
Editor, Jurnal RESTI

2 Attachments • Scanned by Gmail

J. Riyono <jokoriyono@trisakti.ac.id> 4:11 PM (2 hours ago)

to rita

Dear Ms. Rita Komalasari.

We would like to convey the production stage revisions to our manuscript. We have included the revised file, feedback, and Turnitin proof in this email. We sincerely hope you find this information helpful. Thank you for your cooperation.

Regards.

Joko Riyono.

REVISIONS FROM REVIEWER A

1. The abstract is somewhat dense, with several long sentences that could be shortened to improve readability.
   ANSWER:
   The abstract has been revised by improving sentence structure to enhance clarity and readability.

2. The novelty should be clarified by briefly explaining how the tanh function enhances stability.
   ANSWER:
   The novelty has been clarified by adding a brief explanation on how the tanh function enhances stability. Specifically, we have included the following explanation in the manuscript:"To address this issue, this study proposes a Tanh-Based Acceleration Coefficient PSO (TB-PSO), where the acceleration coefficients are modified using the hyperbolic tangent (tanh) function. The smooth and continuous behavior of tanh enables gradual coefficient updates, limits excessive particle velocities, and maintains swarm diversity, thereby improving convergence stability and balancing exploration and exploitation."

3. Including one quantitative performance metric would make the results more convincing.
   ANSWER:
   To strengthen the results, we have added a quantitative performance metric. Specifically, we included comparative results based on the average and standard deviation of the best solutions. As stated in the revised manuscript:
   "In the 10-dimensional experiments, TB-PSO achieves the best overall final ranking based on the average and standard deviation of best solution, ranking first for functions f_3 and f_5, second for f_2 with only a marginal

difference from the best-performing method, and remaining competitive for f_1 and f_4."

4. The description of the 30 dimensional performance should be more specific rather than saying it "slightly declines."

   ANSWER:

   The description of the 30-dimensional performance has been revised to be more specific by replacing the qualitative phrase 'slightly declines' with explicit ranking results. The revised manuscript now states: "These results indicate superior solution quality and stable convergence. For the 30-dimensional benchmark functions, TB-PSO ranks first for f_2, second for f_5, and third for f_1, f_3, and f_4 based on the same evaluation criteria. Although its ranking decreases compared to the 10-dimensional case, TB-PSO remains competitive, reflecting the increased complexity of high-dimensional optimization problems."

5. Consider adding a short paragraph summarizing limitations of existing adaptive PSO methods (TVAC, SCAC, SBAC) to highlight the novelty of TB-PSO more clearly in the introduction.

   ANSWER:

   we have added a short paragraph in the Introduction summarizing the limitations of existing adaptive PSO methods.

   ".... including Time-Varying Acceleration Coefficients [11], Sine-Cosine Acceleration Coefficients [12], Nonlinear Dynamics Acceleration Coefficients [12], and Sigmoid-Based Acceleration Coefficients [8]. These modifications allow for adaptive changes in acceleration coefficients during the optimization process, improving PSO's convergence and solution quality. Among these, the Sigmoid-Based Acceleration Coefficients have shown

particularly strong performance. In previous studies, this method consistently outperformed others across several benchmark functions and was ranked first overall in final performance evaluations [8]. Despite these promising results, the nature of the sigmoid function still introduces relatively abrupt transitions in acceleration values during iterations, which may affect the stability of the swarm's movement in more complex search landscapes. Recognizing this limitation, this study explores whether a smoother functional form could further enhance the adaptive behavior of PSO."

6. Some of the figures can be enlarged a bit
   ANSWER:
   The figures have been revised and enlarged

7. The conclusion is good but can be strengthened by adding a brief summary of why tanh-based adaptation works well and clear future directions (e.g., hybrid methods, real world datasets).
   ANSWER:
   The conclusion has been strengthened by adding a concise explanation of why the tanh-based adaptation is effective, emphasizing its smooth and bounded behavior in maintaining swarm diversity and ensuring stable convergence. The revised conclusion now includes the following summary:
   "...The smooth and continuous nature of the tanh function allows gradual transitions of acceleration values across iterations, which helps maintain swarm diversity and reduces the risk of premature convergence. Moreover, since the tanh function maps inputs to a bounded range of −1 to 1, it prevents excessive velocity updates and contributes to stable convergence behavior. Convergence analysis confirms that TB-PSO satisfies stability criteria, making it suitable for optimization

tasks. Experimental results demonstrate that TB-PSO performs particularly well in 10-dimensional benchmark problems, achieving the 1st rank out of 5 PSO variants based on solution quality and stability. In 30-dimensional problems, TB-PSO remains competitive, ranking 3rd out of 5, indicating its adaptability to increased problem complexity, although broader exploration mechanisms are required for higher-dimensional search spaces...''

8. Consider stating explicitly whether TB-PSO is computationally heavier or comparable to other PSO variants.
   ANSWER:
   In response, we have explicitly clarified the computational complexity of TB-PSO in the revised manuscript. We state that TB-PSO does not introduce significant additional computational overhead compared to other PSO variants.

REVISIONS FROM EDITOR

1. Figure 1 appears blurry. Please replace it with a clearer, higher-resolution version. In addition, ensure that the figure caption uses a font size of 8 pt.

   ANSWER:

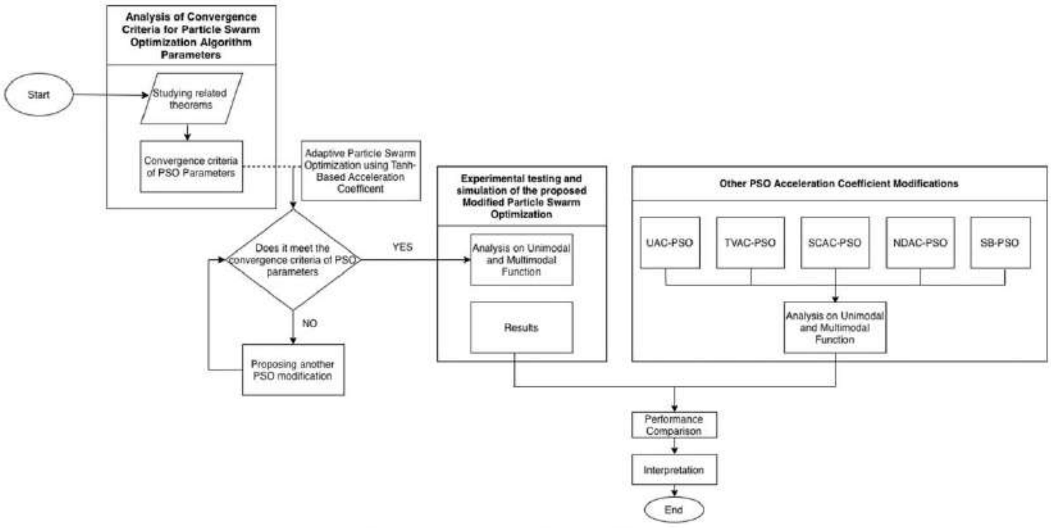

Figure 1. Flowchart of the research

Figure 1. Revision

   Done.

2. Please avoid using terms such as "the following equation" or "the following formula." Instead, refer directly to the equation number. Also, ensure that every equation is properly cited and referred to within the manuscript text.

   ANSWER:

value is achieved. The position and velocity of each particle are updated using equations (1) and (2):

$$x_i^{(t+1)} = v_i^{(t+1)} + x_i^{(t)} \tag{1}$$

$$v_i^{(t+1)} = \omega\, v_i^{(t)} + c_1 r_1 \left(p_{(i,lb)}^{(t)} - x_i^{(t)}\right) + c_2 r_2 \left(p_{gb}^{(t)} - x_i^{(t)}\right) \tag{2}$$

Figure 2. Revision

To evaluate the performance of the proposed TBPSO, a series of experiments were conducted on a set of well-known benchmark functions, covering six global optimization problems. These six functions have been described in the equations (3)-(7). Figure 5. presents the two-dimensional visualization of the five benchmark test functions used. All these functions are designed to be minimized and are labeled as f_1 to f_5, as summarized in Table 2. The table provides the mathematical formulas, number of dimensions, search space boundaries, global optimum values, and the characteristics of each function. This section focuses on analyzing the impact of different acceleration coefficients in the PSO algorithm. The implementation of other methods, such as UACPSO, TVAC-PSO (eq. 8 and 9), SCAC-PSO (eq. 10 and 11), NDAC-PSO (eq.12 and 13), and SB-PSO (eq. 14 dan 15), follows a similar

Figure 3. Revision

Done.

3. Please avoid the use of numbering formats and bullet points throughout the manuscript.
   ANSWER:
   After carefully reviewing the manuscript, we confirmed that numbering formats and bullet points are not used throughout the manuscript.

4. Provide an introductory paragraph before entering any sub-section. For example, Section 3.1 should not appear immediately after Chapter 3 without a preceding introduction.
   ANSWER:

the cognitive component (C_1) is gradually decreased, while the social component (C_2) is increased over time, as described by the following equations:

3. Results and Discussions

While the proposed tanh-based strategy is expected to improve the balance between exploration and

4

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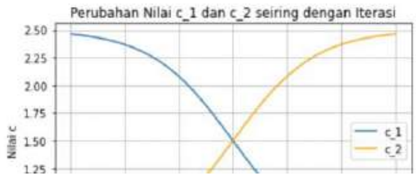
exploitation, any modification of the PSO parameters should also preserve the convergence properties of the algorithm. Therefore, the next subsection analyzes the convergence conditions of the proposed approach to ensure that the resulting particle dynamics remain stable.



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Done.

5. Tables should be presented as tables and should not resemble figures (e.g., Table 2). Please ensure that all tables follow the formatting guidelines specified in the journal template.
   ANSWER:

Table 1. Pseudocode of the Proposed TB-PSO Algorithm

Algorithm 2 : Pseudocode of the proposed TB-PSO Algorithm
Input : w_0: inertia weight (0.7298); $c_{1i}, c_{2i}, c_{1f}, c_{2f}$; N: swarm size; D: swarm dimension; iter_max: maximum iterations
Process: 1. Initialize the swarm particles with random positions and velocities. 2. Evaluate the fitness of the each particle. 3. Identify the personal best (pbest) dan global best (gbest) solutions. 4. **While** iter ≤ iter_max **do** 5. Calculate c_1, c_2 by Eqs. (20-21). 6. **for** n = 1 **to** N **do** 7. Update velocity and position of particles by Eqs.(24)-(25) 8. Ensure boundaries are respected for x_i 9. Evaluate the fitness of the new particle position 10. **If** fitness of x_i is better than $pbest_i$ **then** 11. Update $pbest_i$ with x_i 12. **end if** 13. **If** fitness of x_i is better than $gbest$ **then** 14. Update $gbest$ with x_i 15. **end if** 16. **end for** 17. Update iteration counter 18. **end while**
Output: Gbest particle as the final optimal solution.

Figure 5. Revision

Done.

6. Ensure that all references comply with the IEEE citation style, contain complete bibliographic information, and include active (clickable) DOI links where available.
ANSWER:

References

[1] J. Zhang *et al.*, "Capacity estimation for series-connected battery pack based on partial charging voltage curve segments," *Journal of Energy Storage*, vol. 95, p. 112576, Aug. 2024, doi: https://doi.org/10.1016/j.est.2024.112576.

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Figure 6. Revision

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1. Numbering is still present in the manuscript (see page 4).
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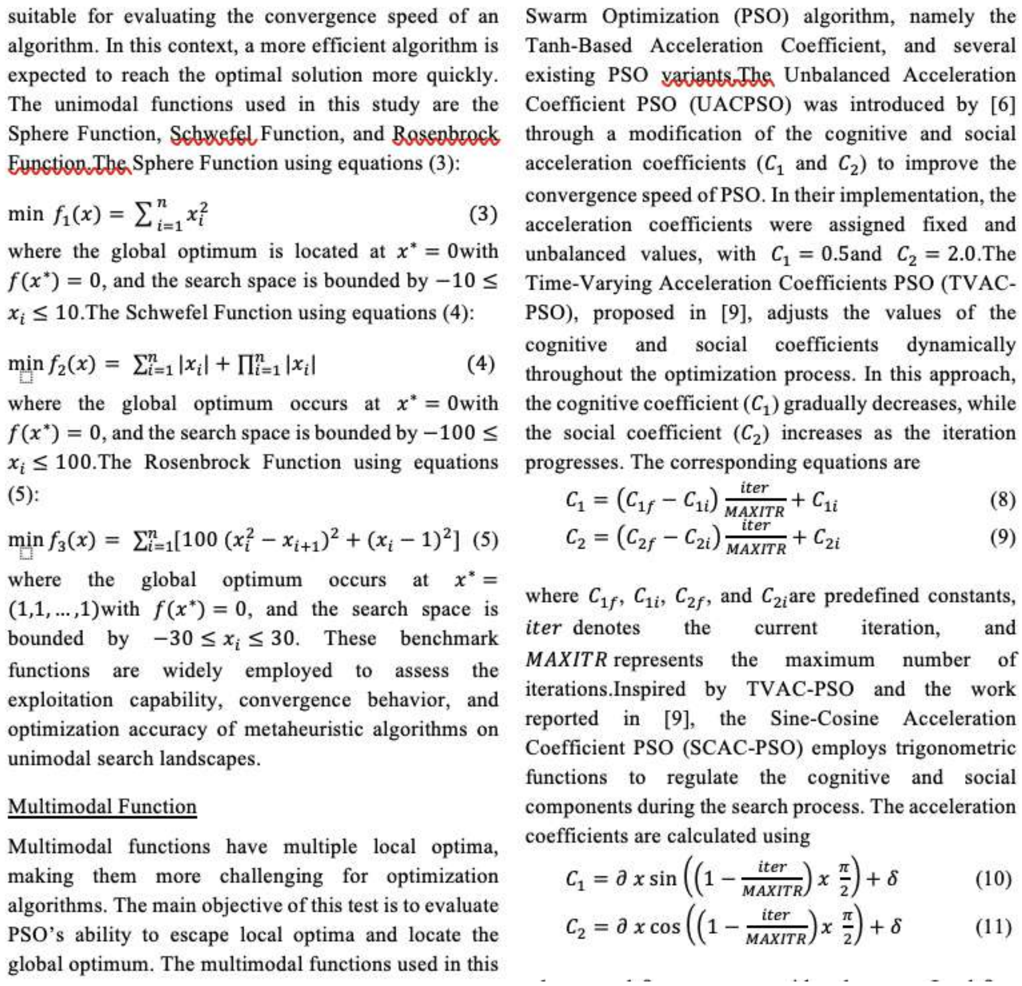

suitable for evaluating the convergence speed of an algorithm. In this context, a more efficient algorithm is expected to reach the optimal solution more quickly. The unimodal functions used in this study are the Sphere Function, Schwefel Function, and Rosenbrock Function.The Sphere Function using equations (3):

$$\min f_1(x) = \sum_{i=1}^{n} x_i^2 \quad (3)$$

where the global optimum is located at $x^* = 0$with $f(x^*) = 0$, and the search space is bounded by $-10 \leq x_i \leq 10$.The Schwefel Function using equations (4):

$$\min f_2(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i| \quad (4)$$

where the global optimum occurs at $x^* = 0$with $f(x^*) = 0$, and the search space is bounded by $-100 \leq x_i \leq 100$.The Rosenbrock Function using equations (5):

$$\min f_3(x) = \sum_{i=1}^{n} [100\,(x_i^2 - x_{i+1})^2 + (x_i - 1)^2] \quad (5)$$

where the global optimum occurs at $x^* = (1,1,\ldots,1)$with $f(x^*) = 0$, and the search space is bounded by $-30 \leq x_i \leq 30$. These benchmark functions are widely employed to assess the exploitation capability, convergence behavior, and optimization accuracy of metaheuristic algorithms on unimodal search landscapes.

Multimodal Function

Multimodal functions have multiple local optima, making them more challenging for optimization algorithms. The main objective of this test is to evaluate PSO's ability to escape local optima and locate the global optimum. The multimodal functions used in this

Swarm Optimization (PSO) algorithm, namely the Tanh-Based Acceleration Coefficient, and several existing PSO variants.The Unbalanced Acceleration Coefficient PSO (UACPSO) was introduced by [6] through a modification of the cognitive and social acceleration coefficients (C_1 and C_2) to improve the convergence speed of PSO. In their implementation, the acceleration coefficients were assigned fixed and unbalanced values, with $C_1 = 0.5$and $C_2 = 2.0$.The Time-Varying Acceleration Coefficients PSO (TVAC-PSO), proposed in [9], adjusts the values of the cognitive and social coefficients dynamically throughout the optimization process. In this approach, the cognitive coefficient (C_1) gradually decreases, while the social coefficient (C_2) increases as the iteration progresses. The corresponding equations are

$$C_1 = (C_{1f} - C_{1i}) \frac{iter}{MAXITR} + C_{1i} \quad (8)$$

$$C_2 = (C_{2f} - C_{2i}) \frac{iter}{MAXITR} + C_{2i} \quad (9)$$

where C_{1f}, C_{1i}, C_{2f}, and $C_{2i}$are predefined constants, $iter$ denotes the current iteration, and $MAXITR$ represents the maximum number of iterations.Inspired by TVAC-PSO and the work reported in [9], the Sine-Cosine Acceleration Coefficient PSO (SCAC-PSO) employs trigonometric functions to regulate the cognitive and social components during the search process. The acceleration coefficients are calculated using

$$C_1 = \partial \, x \sin\left(\left(1 - \frac{iter}{MAXITR}\right) x \ \frac{\pi}{2}\right) + \delta \quad (10)$$

$$C_2 = \partial \, x \cos\left(\left(1 - \frac{iter}{MAXITR}\right) x \ \frac{\pi}{2}\right) + \delta \quad (11)$$

Figure 1. Revision

Done.

2. Please ensure that all equations are properly cited and referred to within the manuscript text.
   ANSWER:

global optimum. The multimodal functions used in this study are the Griewank Function and Ackley Function.The Griewank Function using equations (6):

$$\min f_4(x) = \frac{1}{4000} \sum_{i=1}^{n} (x_i)^2 - \prod_{i=1}^{d} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \qquad (6)$$

where the global optimum is located at $x^* = 0$with $f(x^*) = 0$, and the search space is bounded by $-600 \leq x_i \leq 600$.The Ackley Function using equations (7):

$$\min f_6(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n} cos(2\pi x_i)\right) + 20 + e \qquad (7)$$

Figure 2. Revision

Done.

3. The phrase "is defined as follows" is still used. Please revise the wording and cite the equation directly instead.
ANSWER:

global optimum. The multimodal functions used in this study are the Griewank Function and Ackley Function.The Griewank Function using equations (6):

$$\min f_4(x) = \frac{1}{4000} \sum_{i=1}^{n} (x_i)^2 - \prod_{i=1}^{d} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \qquad (6)$$

where the global optimum is located at $x^* = 0$with $f(x^*) = 0$, and the search space is bounded by $-600 \leq x_i \leq 600$.The Ackley Function using equations (7):

$$\min f_6(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n} cos(2\pi x_i)\right) + 20 + e \qquad (7)$$

Figure 2. Revision

Done.

4. Table 1 is still presented in a figure-like format. In addition, please avoid displaying algorithms or pseudocode. Kindly convert this section into a narrative explanation.
ANSWER:

during the search process. The iteration stops when a stopping criterion is met, or when the convergence value is achieved. The position and velocity of each particle are updated using equations (1) and (2):

$$x_i^{(t+1)} = v_i^{(t+1)} + x_i^{(t)} \tag{1}$$

$$v_i^{(t+1)} = \omega\, v_i^{(t)} + c_1 r_1 \left(p_{(i,lb)}^{(t)} - x_i^{(t)}\right) + c_2 r_2 \left(p_{gb}^{(t)} - x_i^{(t)}\right) \tag{2}$$

Where $x_i^{(t+1)}$ is the position of particle i at generation t+1; $v_i^{(t+1)}$ is the velocity of particle i at generation t+1; $x_i^{(t)}$ is the position of particle i at generation t; $v_i^{(t)}$ is the velocity of particle I at generation t; c_1 and c_2 are acceleration coefficients, which are set to 2 in the original PSO algorithm; ω is the inertia weight; $p_{(i,lb)}^{(t)}$ is the personal best position; r_1 and r_2 are random values in the range [0,1]; $p_{gb}^{(t)}$ is the global best position.

Figure 4. Revision

Done.

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ANSWER:

Table 2. Results of TB-PSO with different acceleration coefficients under D=10

Function	Item	UACPSO	TVAC-PSO	SCAC-PSO	NDAC-PSO	SAC-PSO	TB-PSO
f_1	Avg.	3.538e-39	9.9284e-45	1.5785e-20	4.6945e-65	5.8679e-73	3.3224e-43
	Std.	8.428e-39	3.9978e-44	5.4567e-20	9.2316e-65	1.4079e-72	8.6482e-43
	Rank	5	3	6	2	1	4
f_2	Avg.	103.3333	4.0695e-21	7.3839e-09	4.8592e-08	2.1391	4.8640e-20
	Std.	87.4960	1.5557e-20	1.6545e-08	2.6168e-07	0.0001	8.7043e-20
	Rank	6	1	3	4	5	2
f_3	Avg.	15644.57	2.3721	4.5008	7.2407	6.9532	1.6594
	Std.	33273.91	3.0931	2.5277	18.6422	11.1224	1.4737
	Rank	6	2	3	5	4	1
f_4	Avg.	0.1311	0.0565	0.0695	0.0416	0.0482	0.0542

Table 3. Results of TB-PSO with different acceleration coefficients under D=30

Function	Item	UACPSO	TVAC-PSO	SCAC-PSO	NDAC-PSO	SAC-PSO	TB-PSO
f_1	Avg.	60.00	0.0007	3.0866e-05	1.3887	0.5386	0.0165
	Std.	75.7188	0.0019	4.5051e-05	0.8974	0.5100	0.0349
	Rank	6	2	1	5	4	3
f_2	Avg.	620.2326	10.0128	34.0329	121.5802	112.7581	0.0748
	Std.	285.9189	39.5781	59.1743	57.5216	80.2891	0.1778
	Rank	6	2	3	5	4	1
f_3	Avg.	8024586.7	55.1368	132.4436	8637.22	2438.94	132.834
	Std.	23993091.4	45.8024	120.7221	10601.94	11.1224	143.74
	Rank	6	1	2	5	4	3
f_4	Avg.	69.3386	0.1325	0.0209	2.1649	1.4999	0.3633
	Std.	72.5798	0.2176	0.0204	0.8729	0.6209	0.3399

Figure 5. Revision

Done.

Thank You.

REVISIONS FROM EDITOR

Thank you for the revision. The manuscript has improved significantly.

However, I would like to ask about citations [9] and [10]. Are these citations intentionally placed at the beginning of the sentence? In most cases, citations are typically placed at the end of the relevant sentence or statement.

Please review the placement of these citations and revise them if necessary to ensure consistency with the journal's citation style.

ANSWER:

Previous studies proposed a modification to the acceleration coefficients by employing unbalanced values ($C_1 = 0.5$ and $C_2 = 2.5$), which improved convergence performance for specific optimization problems [9]. In addition, dynamically adjusting the acceleration coefficients at each iteration was reported to enhance the algorithm's capability to obtain the global optimum solution [10]. To address this, several approaches have been introduced using both linear and

Thank You.

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ANSWER:

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c_{1f}, c_{2f}, c_{1i}, and c_{2i} are positive constant coefficients, with (c_{1f} and c_{2f} = 2.5 ; c_{1i} and c_{2i} = 0.5). The term "iter" represents the current iteration [18] , while 'iter max' denotes the maximum number of allowed iterations.

Figure 2 visualizes the plot of equations (16) and (17). The value of c_1 gradually decreases per iteration, ranging from 2.5 to 0.5, represented by the blue line. Meanwhile, the value c_2 increases per iteration, ranging from 0.5 to 2.5, shown by the yellow line.

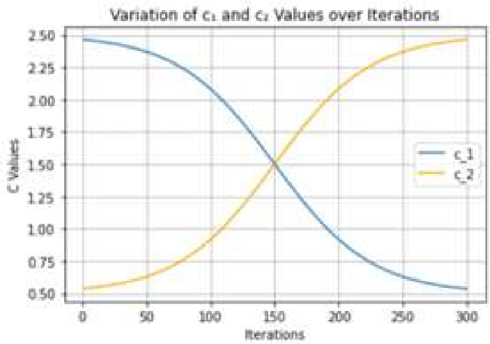

Figure 2. Visualization of c_1 and c_2 Values per Iteration

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Convergence and Empirical Performance of Tanh-Based Adaptive Particle Swarm Optimization

Joko Riyono[1*], Aina Latifa Riyana Putri[2],Sofia Debi Puspa [3], Supriyadi[4], Christina Eni Pujiastuti[5], Fayza Nayla Riyana Putri[6]

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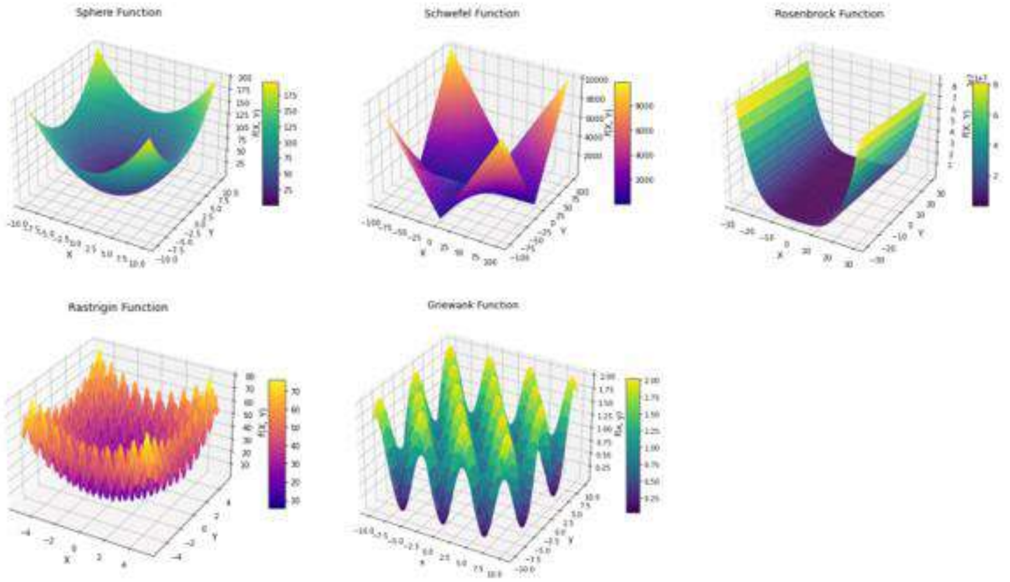

Figure 5. The two-dimensional visualization of the Five Benchmark Test Functions

Thank You.

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Convergence and Empirical Performance of Tanh-Based Adaptive Particle Swarm Optimization

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9 **Abstract**

Particle Swarm Optimization (PSO) is a widely used population-based optimization method but faces challenges in premature convergence, leading to suboptimal solutions. To address this issue, this study proposes a Tanh-Based Acceleration Coefficient PSO (TB-PSO), where the acceleration coefficients are modified using the hyperbolic tangent (tanh) function. The smooth and continuous behavior of tanh enables gradual coefficient updates, limits excessive particle velocities, and maintains swarm diversity, thereby improving convergence stability and balancing exploration and exploitation. The convergence theorem
8 *analysis confirms that TB-PSO meets stability criteria before being evaluated on unimodal and multimodal benchmark functions in 10 and 30 dimensions. Its performance is compared against several PSO variants, including TVAC-PSO, SCAC-PSO, NDAC-PSO, and SAC-PSO. In the 10-dimensional experiments, TB-PSO achieves the best overall final ranking based on the average and standard deviation of best solution, ranking first for functions f_3 and f_5, second for f_2 with only a marginal difference from the best-performing method, and remaining competitive for f_1 and f_4. These results indicate superior solution quality and stable convergence. For the 30-dimensional benchmark functions, TB-PSO ranks first for f_2, second for f_5, and third for f_1, f_3, and f_4 based on the same evaluation criteria. Although its ranking decreases compared to the 10-dimensional case, TB-PSO remains competitive, reflecting the increased complexity of high-dimensional optimization problems. Overall, the results demonstrate that the tanh-based acceleration coefficient modification effectively enhances PSO performance, particularly in lower-dimensional search spaces, while maintaining robustness in higher-dimensional scenarios.*

Keywords: acceleration coefficient; convergence; particle swarm optimization; tanh function

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1. Introduction

Particle Swarm Optimization (PSO) is a population-based metaheuristic inspired by the collective behavior of bird flocks and fish schools. Within this framework, a swarm of particles explores the search space to locate
13 optimal solutions. Each particle, acting as a candidate solution, maintains a position and a velocity vector. These attributes are iteratively modified by incorporating both the individual's historical best performance (pbest) and the global optimum achieved by the entire population (gbest).

Particle Swarm Optimization (PSO) has been widely applied to various optimization problems due to its ability to intelligently explore the search space using a population-based approach [1]. This characteristic allows PSO to achieve more efficient computations and perform well in handling high-dimensional problems compared to other algorithms such as Grid Search [2], Random Search [3], and Bayesian Optimization [4]. However, one of the main challenges of PSO is convergence, as particles in the swarm may become trapped in local optima or undergo inefficient exploration [5] highlighted that PSO has a tendency to generate divergent trajectories, indicating insufficient convergence. Additionally, PSO particles often converge prematurely to a stable state, leading to suboptimal solutions trapped in local optima [6], [7]. Consequently, numerous studies have been conducted to enhance the performance of PSO, particularly by modifying the acceleration coefficients (C_1 and C_2), which play a crucial role in balancing the exploration and exploitation of the search space [8]. Proper adjustment of these coefficients can improve convergence speed and solution quality.

Previous studies proposed a modification to the acceleration coefficients by employing unbalanced values ($C_1 = 0.5$ and $C_2 = 2.5$), which improved convergence performance for specific optimization problems [9]. In addition, dynamically adjusting the acceleration coefficients at each iteration was reported to enhance the algorithm's capability to obtain the global optimum solution [10]. To address this, several approaches have been introduced using both linear and nonlinear functions to adaptively adjust acceleration coefficients throughout the iterations, including Time-Varying Acceleration Coefficients [11], Sine-Cosine Acceleration Coefficients [12], Nonlinear Dynamics Acceleration Coefficients [12], and Sigmoid-Based Acceleration Coefficients [8]. These modifications allow for adaptive changes in acceleration coefficients during the optimization process, improving PSO's convergence and solution quality. Among these, the Sigmoid-Based Acceleration Coefficients have shown particularly strong performance. In previous studies, this method consistently outperformed others across several benchmark functions and was ranked first overall in final performance evaluations [8]. Despite these promising results, the nature of the sigmoid function still introduces relatively abrupt transitions in acceleration values during iterations, which may affect the stability of the swarm's movement in more complex search landscapes. Recognizing this limitation, this study explores whether a smoother functional form could further enhance the adaptive behavior of PSO.

To this end, this research proposes the use of the hyperbolic tangent (tanh) function as the basis for modifying acceleration coefficients. The smooth and continuous nature of the tanh function enables a more gradual transition between acceleration values in each iteration, which is expected to maintain swarm diversity and prevent premature convergence to local optima [13], [14]. Additionally, the inherent properties of tanh, which map input values to an output range of -1 to 1, help prevent excessive particle velocity updates, thereby maintaining stability throughout the optimization process [11].

This study proposes a modification of PSO hyperparameters, where the acceleration coefficients (C_1 and C_2) are based on the hyperbolic tangent (tanh) function. The proposed hyperparameter modification will be analyzed to verify whether it ensures the convergence of the modified PSO algorithm by applying the convergence criteria theorem from [5]. To demonstrate the effectiveness of the proposed PSO modification, comparisons will be made with several existing approaches, including Time-Varying Acceleration Coefficients, Sine-Cosine Acceleration Coefficients, Nonlinear Dynamics Acceleration Coefficients, and Sigmoid-Based Acceleration Coefficients. Performance evaluation will be conducted using benchmark unimodal and multimodal functions to assess the method's effectiveness under different optimization scenarios and to provide a more thorough numerical analysis. The evaluation focuses on key metrics such as average and standard deviation of best solutions across multiple independent runs. Unimodal functions are used to measure how quickly the method reaches the optimal solution in a relatively simple landscape, while multimodal functions evaluate its ability to escape local optima in more complex search spaces.

Furthermore, this study will also investigate the influence of parameters within the tanh function on the solution search dynamics of PSO to understand the extent to which the tanh function can adapt to the characteristics of different optimization problems. Through this approach, deeper insights into the acceleration mechanism in PSO can be obtained, along with recommendations for optimal hyperparameter tuning across various optimization problem types. Additionally, this study can serve as a reference for researchers and developers of swarm intelligence-based optimization algorithms in addressing challenges related to convergence and solution exploration more effectively.

2. Methods

Based on the limitations discussed in the previous section, this study proposes a modified Particle Swarm Optimization (PSO) algorithm that employs a hyperbolic tangent (tanh)-based formulation for updating the acceleration coefficients. The goal of this modification is to improve the convergence behavior of PSO by ensuring a more balanced trade-off between exploration and exploitation across iterations. Before evaluating the performance of this proposed modification, it is important to first examine the mathematical convergence criteria for PSO and how these criteria relate to parameter settings such as inertia weight (ω), and acceleration coefficients (C_1 and C_2).

The methodology section will sequentially present the analytical methods employed in this study as illustrated in Figure 1. This includes the analysis of PSO convergence criteria, formulation of the proposed tanh-based modification, experimental design using benchmark functions, and performance comparison with other acceleration coefficient strategies.

2.1 Analysis of Convergence Criteria for Particle Swarm Optimization Algorithm Parameters

Particle Swarm Optimization (PSO) was first proposed by [15] as an algorithm for optimizing continuous nonlinear functions. In PSO, each particle independently searches for its best position (personal

20 best or Pbest) while also considering the best position found by the entire swarm (global best or Gbest). This allows the algorithm to converge toward an optimal solution. Each particle shares information about its best
14 position with other particles and adjusts its position and
23 velocity accordingly based on the received information.
10 This means that both the position and velocity of each particle are continuously updated in each iteration during the search process. The iteration stops when a stopping criterion is met, or when the convergence
27 value is achieved. The position and velocity of each particle are updated using equations (1) and (2):

$$x_i^{(t+1)} = v_i^{(t+1)} + x_i^{(t)} \quad (1)$$

$$v_i^{(t+1)} = \omega\, v_i^{(t)} + c_1 r_1 \left(p_{(i,lb)}^{(t)} - x_i^{(t)}\right) + c_2 r_2 \left(p_{gb}^{(t)} - x_i^{(t)}\right) \quad (2)$$

Where $x_i^{(t+1)}$ is the position of particle i at generation t+1; $v_i^{(t+1)}$ is the velocity of particle i at generation t+1; $x_i^{(t)}$ is the position of particle i at generation t; $v_i^{(t)}$ is the velocity of particle I at generation t; c_1 and c_2 are acceleration coefficients, which are set to 2 in the original PSO algorithm; ω is the inertia weight; $p_{(i,lb)}^{(t)}$ is the personal best position; r_1 and r_2 are random values in the range [0,1]; $p_{gb}^{(t)}$ is the global best position.

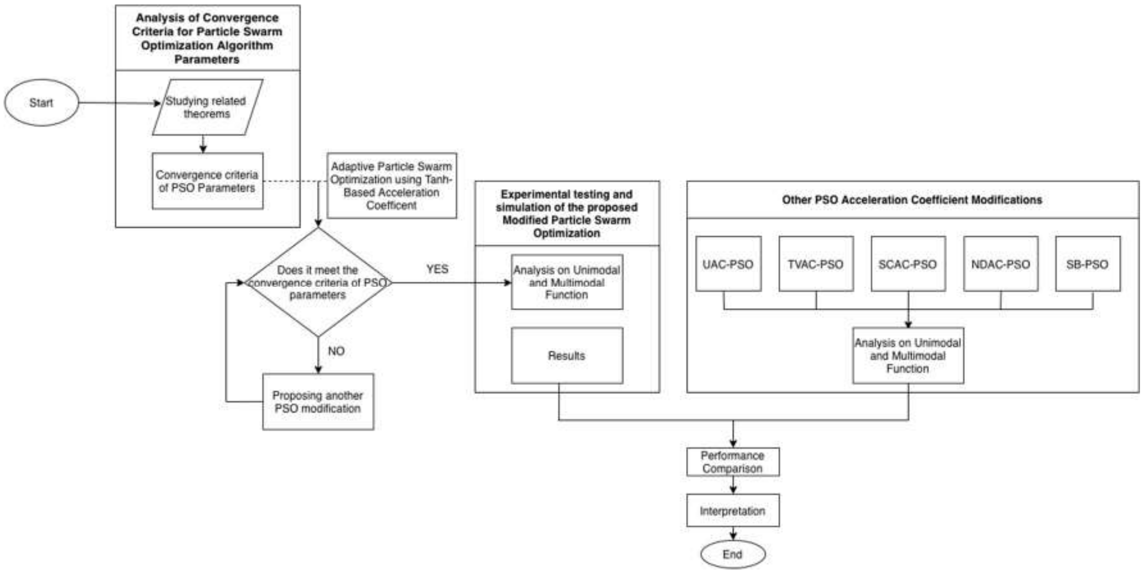

Figure 1. Flowchart of the research

The original Particle Swarm Optimization (PSO) algorithm has several drawbacks, as highlighted by studies such as [6], [7]. These studies indicate that PSO particles tend to converge prematurely to a stable state, leadng to the solutions being trapped in local optima. Furthermore, the convergence of population-based algorithms such as PSO has been reported to depend on an appropriate balance between exploration and exploitation of the search space, enabling particles to move toward the global optimum solution [16]

The convergence of PSO toward the global optimal solution is discussed in the following theorem.

26 Theorem 1. A particle in the Particle Swarm Optimization (PSO) algorithm was shown to converge to a stable point given by $\frac{c_1 p_{(i,lb)}^{(t)} + c_2 p_{gb}^{(t)}}{c_1 + c_2}$, provided that $\max\{|\lambda_1|, |\lambda_2|\} < 1$ where λ_1 and λ_2 are the eigenvalues describing the dynamics of a simple PSO system with inertia weight (ω) [5] .

Based on this theorem, if ω, c_1, c_2 are chosen in such a way: $\frac{c_1+c_2}{2} - 1 < \omega$ and $0 < c_1 + c_2$ that the condition $max\{||\lambda_1||, ||\lambda_2||\} < 1$ is satisfied, then the system guarantees convergence to the stable point. It can be observed that in the original Particle Swarm Optimization (PSO), the chosen values of $c_1 = c_2 = 2$, and $w = 1$ do not satisfy the convergence criteria for PSO parameters. This is because $c_1 + c_2 = 2 + 2 = 4 > 0$ and $\frac{c_1+c_2}{2} - 1 = \frac{2+2}{2} - 1 = 1 = w$. This seemingly implies that the original PSO equation produces a divergent trajectory [17]. Consequently, this raises concerns regarding the application of the original PSO in real-world problems. The trajectory divergence suggests that the original PSO does not provide adequate convergence results. To address this issue, this study focuses on modifying the acceleration coefficients to achieve a better balance between exploration and exploitation. At this stage, we will examine whether the proposed tanh-based acceleration coefficient modification for the Particle Swarm Optimization (PSO) algorithm, as shown below, satisfies the PSO convergence criteria stated in Theorem 2.1. Specifically, we aim to verify whether $max\{||\lambda_1||, ||\lambda_2||\} < 1$ ensuring that the particle search process toward personal best and global best is guaranteed to achieve convergence.

2.2 Experimental Testing and Simulation of the Proposed Modified Particle Swarm Optimization (PSO) Algorithm

This study also conducts an empirical analysis through a series of experimental tests to evaluate the effectiveness of the proposed acceleration coefficient modification. The experiments are carried out by applying the modified PSO algorithm to various standard benchmark functions in optimization. Testing is performed using two main categories of objective functions: unimodal functions and multimodal functions. The selection of these functions aims to assess the convergence capability and effectiveness of the proposed method in finding optimal solutions across different optimization scenarios.

Unimodal functions are objective functions with a single global optimum, making them particularly suitable for evaluating the convergence speed of an algorithm. In this context, a more efficient algorithm is expected to reach the optimal solution more quickly. The unimodal functions used in this study are the Sphere Function, Schwefel Function, and Rosenbrock Function.The Sphere Function using Equation 3.

$$\min\ f_1(x) = \sum_{i=1}^{n} x_i^2 \tag{3}$$

The global optimum is located at $x^* = 0$with $f(x^*) = 0$, and the search space is bounded by $-10 \le x_i \le 10$.The Schwefel Function using Equations 4.

$$\min\ f_2(x) = \sum_{i=1}^{n} |\, x_i \,| + \prod_{i=1}^{n} |\, x_i \,| \tag{4}$$

where the global optimum occurs at $x^* = 0$with $f(x^*) = 0$, and the search space is bounded by $-100 \le x_i \le 100$.The Rosenbrock Function using Equation 5.

$$\min f_3(x) = \sum_{i=1}^{n}[100\,(x_i^2 - x_{i+1})^2 + (x_i - 1)^2] \tag{5}$$

The global optimum occurs at $x^* = (1,1,\ldots,1)$with $f(x^*) = 0$, and the search space is bounded by $-30 \le x_i \le 30$. These benchmark functions are widely employed to assess the exploitation capability, convergence behavior, and optimization accuracy of metaheuristic algorithms on unimodal search landscapes.

Multimodal functions have multiple local optima, making them more challenging for optimization algorithms. The main objective of this test is to evaluate PSO's ability to escape local optima and locate the global optimum. The multimodal functions used in this study are the Griewank Function and Ackley Function.The Griewank Function using Equations 6.

$$\min f_4(x) = \frac{1}{4000}\sum_{i=1}^{n}(x_i)^2 - \prod_{i=1}^{d}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \tag{6}$$

The global optimum is located at $x^* = 0$with $f(x^*) = 0$, and the search space is bounded by $-600 \le x_i \le 600$.The Ackley Function using Equations 7.

$$\min f_6(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e \tag{7}$$

The global optimum occurs at $x^* = 0$with $f(x^*) = 0$, and the search space is bounded by $-600 \le x_i \le 600$. These multimodal benchmark functions contain numerous local optima, making them suitable for evaluating the exploration capability and robustness of optimization algorithms in avoiding premature convergence and locating the global optimum.

2.3 Performance Comparison with Other PSO Acceleration Coefficient Modifications

At this stage, a performance comparison is carried out between the proposed modification of the Particle Swarm Optimization (PSO) algorithm, namely the Tanh-Based Acceleration Coefficient, and several existing PSO variants. The Unbalanced Acceleration Coefficient PSO (UACPSO) was introduced by [6] through a modification of the cognitive and social acceleration coefficients (C_1 and C_2) to improve the convergence speed of PSO. In their implementation, the acceleration coefficients were assigned fixed and unbalanced values, with $C_1 = 0.5$and $C_2 = 2.0$.The Time-Varying Acceleration Coefficients PSO (TVAC-PSO), proposed in [9], adjusts the values of the cognitive and social coefficients dynamically throughout the optimization process. In this approach, the cognitive coefficient (C_1) gradually decreases, while the social coefficient (C_2) increases as the iteration progresses. The corresponding equations are shown in Equations 8 and 9.

$$C_1 = (C_{1f} - C_{1i})\frac{iter}{MAXITR} + C_{1i} \tag{8}$$

$$C_2 = (C_{2f} - C_{2i})\frac{iter}{MAXITR} + C_{2i} \tag{9}$$

C_{1f}, C_{1i}, C_{2f}, and $C_{2i}$are predefined constants, $iter$ denotes the current iteration, and $MAXITR$ represents the maximum number of iterations. Inspired by TVAC-PSO and the work reported in [9], the Sine-Cosine Acceleration Coefficient PSO (SCAC-PSO) employs trigonometric functions to regulate the cognitive and social components during the search process. The acceleration coefficients are calculated using Equations 10 and 11.

$$C_1 = \partial\ x \sin\left(\left(1 - \frac{iter}{MAXITR}\right) x\ \frac{\pi}{2}\right) + \delta \tag{10}$$

$$C_2 = \partial\ x \cos\left(\left(1 - \frac{iter}{MAXITR}\right) x\ \frac{\pi}{2}\right) + \delta \tag{11}$$

$\alpha$and $\delta$are constants with values $\alpha = 2$and $\delta = 0.5$.The Nonlinear Dynamics Acceleration Coefficient PSO (NDAC-PSO) introduces nonlinear adjustment mechanisms for the acceleration coefficients to balance exploration and exploitation more effectively. The cognitive and social coefficients are updated according to Equations 12 and 13.

$$C_1 = -(C_{1f} - C_{1i})\left(\frac{iter}{MAXITR}\right)^2 + C_{1f} \tag{12}$$

$$C_2 = C_{1i}\ x \left(1-\frac{iter}{MAXITR}\right)^2 + C_{1f}\ x\ \frac{iter}{MAXITR} \quad (13)$$

C_{1f} and C_{1i} are positive constants with values 2.5and 0.5, respectively, $iter$denotes the current iteration, and $MAXITR$is the maximum number of iterations.The Sigmoid-Based Acceleration Coefficient PSO (SAC-PSO) utilizes a sigmoid function to generate nonlinear variations of the acceleration coefficients throughout the optimization process. The coefficients are determined using Equations 14 and 15.

$$C_1 = \frac{1}{1+e^{(-\lambda \cdot \frac{iter}{MAXITR})}} + 2(C_{1f}-C_{1i})(\frac{iter}{MAXITR}-1)^2 \quad (14)$$

$$C_2 = \frac{1}{1+e^{(-\lambda \cdot \frac{iter}{MAXITR})}} + (C_{1f}-C_{1i})(\frac{iter}{MAXITR})^2 \quad (15)$$

λ is a control parameter used to regulate the sigmoid-based acceleration coefficient ($\lambda = 0.0001$). The parameters C_{1f} and C_{1i} are positive constants with values of 2.5 and 0.5, respectively. The terms $iter$ and $MAXITR$ denote the current iteration and the maximum number of iterations. These PSO variants are employed as benchmark methods to evaluate the effectiveness of the proposed Tanh-Based Acceleration Coefficient in terms of convergence speed, solution quality, and optimization robustness. The experiments were conducted by applying each method to the unimodal and multimodal benchmark functions described previously. The results obtained from each PSO variant were then compared to assess convergence characteristics and the stability of the final solutions. Through this comparative analysis, the study seeks to determine the effectiveness of the proposed acceleration coefficient modification in improving PSO performance across a variety of optimization problems.

3. Results and Discussions

While the proposed tanh-based strategy is expected to improve the balance between exploration and exploitation, any modification of the PSO parameters should also preserve the convergence properties of the algorithm. Therefore, the next subsection analyzes the convergence conditions of the proposed approach to ensure that the resulting particle dynamics remain stable.

3.1 Tanh-Based Acceleration Coefficient

The performance of PSO heavily depends on maintaining a proper balance between exploration and exploitation. Therefore, the right ratio between these two aspects must be carefully established. In general, PSO should begin with strong exploration to widely search the solution space and gradually shift toward exploitation to refine the optimal solution with greater precision.

Based on this principle, various time-varying strategies have been developed to adjust PSO parameters, including the acceleration coefficients C_1 and C_2. As previously discussed, C_1 influences local exploration tendencies, while C_2 determines the level of global exploitation. Consequently, dynamically adjusting these coefficients is crucial for improving the balance between exploration and exploitation in PSO.

In this study, the proposed modification of the acceleration coefficients in the Particle Swarm Optimization (PSO) algorithm based on the tanh function is defined as Equations 16 and 17.

$$c_1(iter) = 0{,}5.\left(\tanh\left(2.(c_{1f}-c_{1i}).\left(\frac{iter\ max - iter}{iter\ max} - 0{,}5\right)\right)+1\right).(c_{1f}-c_{1i}) + c_{1i} \quad (16)$$

$$c_2(iter) = 0{,}5.\left(\tanh\left(2.(c_{2f}-c_{2i}).\left(\frac{iter}{iter\ max} - 0{,}5\right)\right)+1\right).(c_{2f}-c_{2i}) + c_{2i} \quad (17)$$

$c_{1f}, c_{2f}, c_{1i},$ and c_{2i} are positive constant coefficients, with (c_{1f} and $c_{2f} = 2{,}5$; c_{1i} and $c_{2i} = 0{,}5$). The term "iter" represents the current iteration [18] , while 'iter max' denotes the maximum number of allowed iterations.

Figure 2 visualizes the plot of equations (16) and (17). The value of c_1 gradually decreases per iteration, ranging from 2.5 to 0.5, represented by the blue line. Meanwhile, the value c_2 increases per iteration, ranging from 0.5 to 2.5, shown by the yellow line.

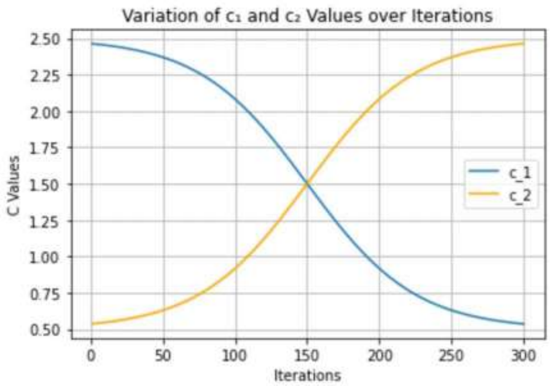

Figure 2. Visualization of c_1 and c_2 Values per Iteration

The proposed strategy enables a smoother transition from exploration to exploitation. During the early stages of the search, c_1 starts at a high value, allowing particles to explore the search space more broadly. Conversely, c_2 begins with a lower value, preventing premature exploitation. As the iterations progress, c_1 gradually decreases while c_2 increases [18]. This dynamic adjustment is designed to create a nonlinear and more natural transition from exploration to exploitation compared to linear-based approaches.

*3.2 Convergence Analysis of Tanh-Based Acceleration Coefficients in Particle Swarm Optimiz*ation

As previously explained, the conditions ensuring that each particle in the Particle Swarm Optimization algorithm converges to a stable point were analyzed. Based on the proposed modification, the values obtained are $c_1 = 0,5$; $c_2 = 2,5$; w = 0.7298 [19], considering that c_1 and c_2 represent the upper bounds of φ_1 and φ_2. These values were verified using Theorem 1. The results indicate that the selected values satisfy the convergence criteria of the Particle Swarm Optimization algorithm, as they meet the conditions $c_1 + c_2 = 0,5 + 2,5 = 3,5 > 0$ and $\frac{c_1+c_2}{2} - 1 = \frac{0,5+2,5}{2} - 1 = 1,5 - 1 = 0,5 < 0,7298$.

Further explanation can be obtained by calculating the value of $\max\{\|\lambda_1\|, \|\lambda_2\|\}$ using the equations for λ_1 and λ_2. As previously discussed, considering the stochastic components with $\varphi_1 = c_1 r_1$ and $\varphi_2 = c_2 r_2$, where $r_1, r_2 \sim U(0,1)$, it is evident that $0 < \varphi_1 + \varphi_2 < 3$ when $c_1 = 0,5$; $c_2 = 2,5$. Next, by substituting $\varphi = \varphi_1 + \varphi_2$ into the equations for λ_1 and λ_2, two sets of calculations are obtained: one for real values of γ and one for complex values of γ. Consider the case where γ is $\mathbb{R}$, when $\varphi \in [0;\ 0,021233349266117]$as shown in Equation 18.

$$max\ \{\|\lambda_1\|, \|\lambda_2\|\} \approx \frac{1,7298-\varphi\pm\sqrt{\varphi^2-3,4596\varphi \quad ,073}}{4} \tag{18}$$

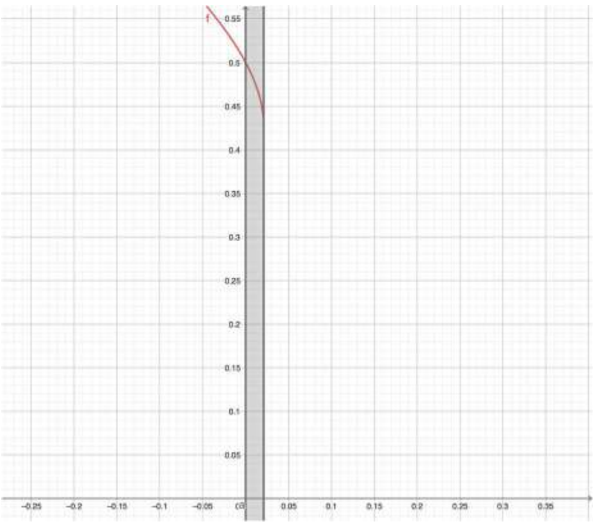

Figure 3a. Graphical Visualization of $\|\lambda_1\|$ and $\|\lambda_1\|$ for $\gamma \in \mathbb{R}$ (Positive Case)

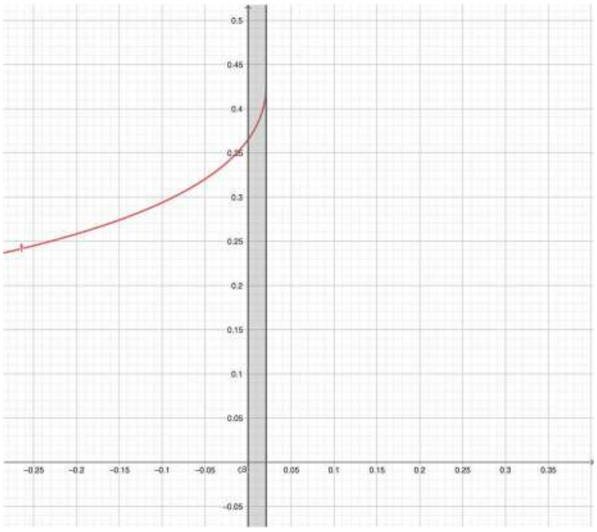

Figure 3b. Graphical Visualization of $\|\lambda_1\|$ and $\|\lambda_1\|$ for Real $\gamma \in \mathbb{R}$ (Negative Case)

Figures 3a and 3b illustrate the solution set for $\|\lambda_1\|$ and $\|\lambda_1\|$ when $\gamma \in \mathbb{R}$. The red line in Figure 3a represents the function: $\max\{\|\lambda_1\|, \|\lambda_2\|\} \approx \frac{1,7298- \quad \sqrt{\varphi^2-3,4596\varphi+0,073}}{4}$, Within the range $\varphi \in [0;\ 0,021233349266117]$, the value of $\max\{\|\lambda_1\|, \|\lambda_2\|\}$ remains below 0.5, satisfying the convergence criteria of the Particle Swarm Optimization algorithm, which requires $\max\{\|\lambda_1\|, \|\lambda_2\| b\} < 1$. Similarly, the red line in Figure 3b represents the function: $\max\{\|\lambda_1\|, \|\lambda_2\|\} \approx \frac{1,7298- \quad \sqrt{\varphi^2-3,4596\varphi+0,073}}{4}$, Within the range $\varphi \in [0;\ 0,021233349266117]$, the value of $\max\{\|\lambda_1\|, \|\lambda_2\|\}$ also remains below 0.5, further confirming that the proposed modification satisfies the convergence criteria for the Particle Swarm Optimization algorithm. Now, Consider the case where γ is $\mathbb{C}$, when $\varphi \in (0,021233349266117; 3]$as shown in Equation 19.

$$\|\lambda_1\| = \|\lambda_2\| = \sqrt{\frac{(1,7298-\varphi)^2}{4} + \frac{-\varphi^2+3,4596\varphi-0,073}{4}} \approx 0,8542845 \tag{19}$$

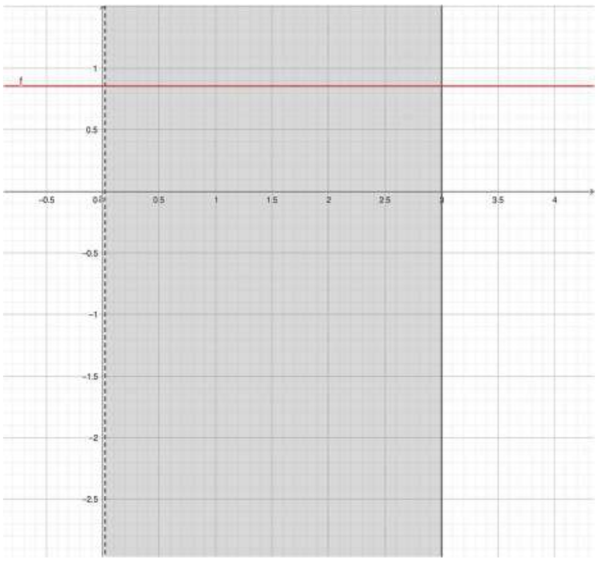

Figure 4. Graphical Visualization of $\|\lambda_1\|$ and $\|\lambda_1\|$ for $\gamma \in \mathbb{C}$

Figure 4 illustrates the solution set for $\|\lambda_1\|$ and $\|\lambda_2\|$ when $\gamma \in \mathbb{C}$. The red line in Figure 4 represents the function have been described in Equation (19):

$$\max\{\|\lambda_1\|, \|\lambda_2\|\} \approx \sqrt{\frac{(1{,}7298- \ )^2}{4} + \frac{-\varphi^2+3{,}4596\varphi-0{,}073}{4}} \quad (19)$$

Within the range $\varphi \in (0{,}021233349266117; 3]$, the value of $\max\{\|\lambda_1\|, \|\lambda_2\|\}$ is approximately 0.8542845, which satisfies the convergence criterion of the Particle Swarm Optimization algorithm, as it remains below the condition $\max\{\|\lambda_1\|, \|\lambda_2\|\} < 1$. Thus, it can be observed that the proposed modification ensures the generation of a convergent trajectory.

3.3 Experimental Results and Analysis

To evaluate the performance of the proposed TBPSO, a series of experiments were conducted on a set of well-known benchmark functions, covering six global optimization problems. These six functions have been described in the equations (3)-(7). Figure 5. presents the two-dimensional visualization of the five benchmark test functions used. All these functions are designed to be minimized and are labeled as f_1 to f_5, as summarized in Table 1. The table provides the mathematical formulas, number of dimensions, search space boundaries, global optimum values, and the characteristics of each function. This section focuses on analyzing the impact of different acceleration coefficients in the PSO algorithm. The implementation of other methods, such as UACPSO, TVAC-PSO (eq. 8 and 9), SCAC-PSO (eq. 10 and 11), NDAC-PSO (eq.12 and 13), and SB-PSO (eq. 14 dan 15), follows a similar procedure to TBPSO, with the main difference lying in the use of different acceleration coefficients.

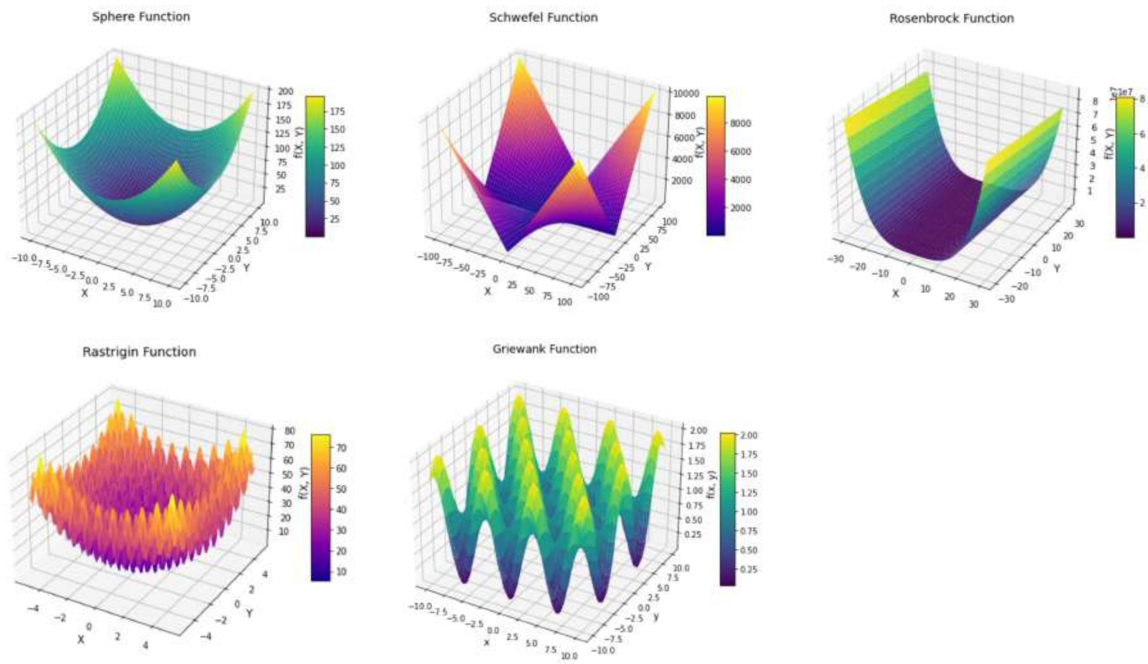

Figure 5. The two-dimensional visualization of the Five Benchmark Test Functions

Table 1. Properties of the Test Function

Test Functions	Dimensions	Search Range	Global Optimum	Properties
Sphere (f1)	10/30	[-10,10]^D	0	Unimodal
Schwefel (f2)	10/30	[-100,100]^D	0	Unimodal
Rosenbrock (f3)	10/30	[-30,30]^D	0	Unimodal
Griewank (f4)	10/30	[-600,600]^D	0	Multimodal

Ackley (f5)	10/30	[-32,32]^D	0	Multimodal

The implementation of other methods, such as UACPSO, TVAC-PSO, SCAC-PSO, NDAC-PSO, and SB-PSO, follows a similar procedure to TBPSO, with the main difference lying in the use of different acceleration coefficients.

21 The experimental setup in this study is defined as follows: the swarm size is set to N = 40 [20], and each benchmark function is executed independently 30 times, with each execution consisting of 1000 iterations. All PSO algorithms are terminated upon reaching the predefined maximum number of iterations to ensure a fair comparison across different methods and to control computational cost, as unlimited execution may lead to excessive runtime without guaranteeing significant improvement in solution quality, as commonly practiced in heuristic optimization studies [21]. The performance evaluation of TB-PSO is conducted using commonly used optimization metrics, namely the best solution, average solution, and standard deviation. The best solution represents the lowest (or highest, depending on the problem) objective function value achieved across all runs. The average solution provides insight into the algorithm's general performance over multiple runs, which is important because metaheuristic algorithms like PSO are stochastic [22] in nature and may yield different results in each execution. By observing the average, we can assess whether the algorithm consistently finds good solutions or only performs well occasionally. The standard deviation, on the other hand, indicates the stability or robustness of the algorithm [23]. A low standard deviation means the results are tightly clustered around the average, suggesting the algorithm performs reliably across runs. A high standard deviation implies high variability, which may indicate sensitivity to initial conditions or instability in convergence. These metrics assess the effectiveness of TB-PSO in solving unimodal and multimodal benchmark functions compared to other PSO methods, particularly in terms of result stability.

To further evaluate the advantages of the proposed PSO modification in this study, TB-PSO is compared with five other PSO variants in the table, including UAPSO, TVAC-PSO, SCAC-PSO, NDAC-PSO, SB-PSO, and TB-PSO. It is important to note that the dimensionality of all benchmark functions is set to 10 and 30. The average best solution (Avg.) and the standard deviation of the best solution (Std.) are used to measure performance, with the best results in the comparison highlighted in bold.

From the results obtained for function dimensions of 10 on Table 2, it can be observed that although TB-PSO ranks fourth in terms of average best solution (Avg.) for f_1, it secures the top rank twice for f_3 and f_5. For f_2, it ranks second, with a minimal difference compared to TVAC-PSO, which holds the first position. Similarly, for f_4, TB-PSO ranks third, with a slight difference compared to NDAC-PSO in first place and SB-PSO in second. Overall, TB-PSO achieves the best final ranking among all methods, indicating superior performance in terms of average best solution and standard deviation.

15 Table 2. Results of TB-PSO with different acceleration coefficients under D=10

Function	Item	UACPSO	TVAC-PSO	SCAC-PSO	NDAC-PSO	SAC-PSO	TB-PSO
f_1	Avg.	3.538e-39	9.9284e-45	1.5785e-20	4.6945e-65	5.8679e-73	3.3224e-43
	Std.	8.428e-39	3.9978e-44	5.4567e-20	9.2316e-65	1.4079e-72	8.6482e-43
	Rank	5	3	6	2	1	4
f_2	Avg.	103.3333	4.0695e-21	7.3839e-09	4.8592e-08	2.1391	4.8640e-20
	Std.	87.4960	1.5557e-20	1.6545e-08	2.6168e-07	0.0001	8.7043e-20
	Rank	6	1	3	4	5	2
f_3	Avg.	15644.57	2.3721	4.5008	7.2407	6.9532	1.6594
	Std.	33273.91	3.0931	2.5277	18.6422	11.1224	1.4737
	Rank	6	2	3	5	4	1
f_4	Avg.	0.1311	0.0565	0.0695	0.0416	0.0482	0.0542
	Std.	0.0675	0.0307	0.0355	0.0258	0.0313	0.0273
	Rank	6	4	5	1	2	3
f_5	Avg.	0.0385	4.1152	5.4052	4.2337	5.6547	4.70e-15
	Std.	0.2074	6.3773	4.0718	8.8620	1.7724	1.42e-15
	Rank	2	3	5	4	6	1
Avg rank		5	2.6	4.4	3.2	3.6	2.2
Final rank		6	2	5	3	4	1

For the 30-dimensional functions on Table 4, TB-PSO ranks first once for f_2. It secures the second position for f_5, just behind SCAC-PSO. Meanwhile, for f_1, f_3, and f_4, TB-PSO ranks third. Although TB-PSO's ranking is not as high in the 30-dimensional case as in the 10-dimensional one, it still demonstrates competitive results compared to other PSO variants. This decline in performance does not imply that TB-PSO is ineffective; rather, it highlights the increased complexity of high-dimensional optimization, which requires broader exploration strategies. Such performance degradation is a well-documented challenge in PSO-based optimization methods, especially in high-dimensional search spaces [24], [25] where premature convergence or loss of diversity often occurs. In comparison, previous studies such as [8] have also reported that their proposed PSO variants showed performance drops when scaling from 10 to 30 dimensions, emphasizing that maintaining a balance between exploration and exploitation becomes more difficult as dimensionality increases.

Table 3. Results of TB-PSO with different acceleration coefficients under D=30

Function	Item	UACPSO	TVAC-PSO	SCAC-PSO	NDAC-PSO	SAC-PSO	TB-PSO
f_1	Avg.	60.00	0.0007	3.0866e-05	1.3887	0.5386	0.0165
	Std.	75.7188	0.0019	4.5051e-05	0.8974	0.5100	0.0349
	Rank	6	2	1	5	4	3
f_2	Avg.	620.2326	10.0128	34.0329	121.5802	112.7581	0.0748
	Std.	285.9189	39.5781	59.1743	57.5216	80.2891	0.1778
	Rank	6	2	3	5	4	1
f_3	Avg.	8024586.7	55.1368	132.4436	8637.22	2438.94	132.834
	Std.	23993091.4	45.8024	120.7221	10601.94	11.1224	143.74
	Rank	6	1	2	5	4	3
f_4	Avg.	69.3386	0.1325	0.0209	2.1649	1.4999	0.3633
	Std.	72.5798	0.2176	0.0204	0.8729	0.6209	0.3399
	Rank	6	2	1	5	4	3
f_5	Avg.	14.5509	2.2814	0.0729	5.1091	3.3869	1.8031
	Std.	6.0579	0.6517	0.0592	1.0914	0.8370	0.6055
	Rank	6	3	1	5	4	2
Avg rank		6	2	1.6	5	4	2.4
Final rank		6	2	1	5	4	3

The key factor influencing TB-PSO's performance is the tanh-based acceleration mechanism, which provides a controlled transition from exploration to exploitation. In lower dimensions, this strategy has proven highly effective in achieving rapid convergence without compromising solution quality. However, in higher dimensions, additional modifications may be required to enhance exploration and prevent convergence to suboptimal solutions. Minor refinements, such as more dynamic parameter adaptation or additional search mechanisms, could further strengthen TB-PSO's capability in handling optimization across different dimensional scenarios. Overall, these results indicate that the proposed TB-PSO modification offers significant advantages, particularly in lower-dimensional search spaces. With further refinements, the method has the potential to become a more flexible and effective optimization solution, even for high-dimensional problems.

For future research, it is recommended to apply TB-PSO to real-world optimization problems, such as scheduling, energy management, or weather prediction with complex variables. Testing the algorithm in practical situations will help assess how well the tanh-based approach works in dynamic environments and may reveal ways to improve the method so it becomes more adaptive and effective for real-world applications.

4. Conclusions

This study proposes a Tanh-Based Particle Swarm Optimization (TB-PSO) method that modifies the acceleration coefficients using the hyperbolic tangent (tanh) function to improve the balance between exploration and exploitation. The smooth and continuous nature of the tanh function allows gradual transitions of acceleration values across iterations, which helps maintain swarm diversity and reduces the risk of premature convergence. Moreover, since the tanh function maps inputs to a bounded range of −1 to 1, it prevents excessive velocity updates and contributes to stable convergence behavior. Convergence analysis confirms that TB-PSO satisfies stability criteria, making it suitable for optimization tasks. Experimental results demonstrate that TB-PSO performs particularly well in 10-dimensional benchmark problems, achieving the 1st rank out of 5 PSO variants based on solution quality and stability. In 30-dimensional problems, TB-PSO remains competitive, ranking 3rd out of 5, indicating its adaptability to increased problem complexity, although broader exploration mechanisms are required for higher-dimensional search spaces.In terms of computational complexity, TB-PSO does not introduce significant additional overhead compared to others PSO variants. Furthermore, applying TB-PSO to real-world optimization problems and benchmark datasets would provide deeper insights into its practical effectiveness and scalability.

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Convergence and Empirical Performance of Tanh-Based Adaptive Particle Swarm Optimization

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Abstract

Particle Swarm Optimization (PSO) is a widely used population-based optimization method but faces challenges in premature convergence, leading to suboptimal solutions. To address this issue, this study proposes a Tanh-Based Acceleration Coefficient PSO (TB-PSO), where the acceleration coefficients are modified using the hyperbolic tangent (tanh) function. The smooth and continuous behavior of tanh enables gradual coefficient updates, limits excessive particle velocities, and maintains swarm diversity, thereby improving convergence stability and balancing exploration and exploitation. The convergence theorem analysis confirms that TB-PSO meets stability criteria before being evaluated on unimodal and multimodal benchmark functions in 10 and 30 dimensions. Its performance is compared against several PSO variants, including TVAC-PSO, SCAC-PSO, NDAC-PSO, and SAC-PSO. In the 10-dimensional experiments, TB-PSO achieves the best overall final ranking based on the average and standard deviation of best solution, ranking first for functions f_3 and f_5, second for f_2 with only a marginal difference from the best-performing method, and remaining competitive for f_1 and f_4. These results indicate superior solution quality and stable convergence. For the 30-dimensional benchmark functions, TB-PSO ranks first for f_2, second for f_5, and third for f_1, f_3, and f_4 based on the same evaluation criteria. Although its ranking decreases compared to the 10-dimensional case, TB-PSO remains competitive, reflecting the increased complexity of high-dimensional optimization problems. Overall, the results demonstrate that the tanh-based acceleration coefficient modification effectively enhances PSO performance, particularly in lower-dimensional search spaces, while maintaining robustness in higher-dimensional scenarios.

Keywords: acceleration coefficient; convergence; particle swarm optimization; tanh function

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1. Introduction

Particle Swarm Optimization (PSO) is a population-based optimization technique that mimics the cooperative movement patterns observed in groups of birds and schools of fish. Within this framework, a swarm of particles explores the search space to locate optimal solutions. Each particle, acting as a candidate solution, maintains a position and a velocity vector. These attributes are iteratively modified by incorporating both the individual's historical best performance (pbest) and the global optimum achieved by the entire population (gbest).

Particle Swarm Optimization (PSO) has been extensively utilized in solving optimization problems because of its capability to effectively search for optimal solutions through a population of interacting particles [1]. This capability enables PSO to perform computationally efficient searches and maintain strong performance when addressing high-dimensional optimization problems, compared with algorithms such as Bayesian Optimization [2], Grid Search [3], and Random Search [4]. However, one of the main challenges of PSO is convergence, as particles in the swarm may become trapped in local optima or undergo inefficient exploration [5] highlighted that PSO has a tendency to generate divergent trajectories, indicating insufficient convergence. Additionally, PSO particles often converge prematurely to a stable state, leading to suboptimal solutions trapped in local optima [6], [7].

Consequently, numerous studies have been conducted to enhance the performance of PSO, particularly by modifying the acceleration coefficients (C_1 and C_2), which are essential for maintaining an appropriate balance between exploration and exploitation during the search process [8]. Proper adjustment of these coefficients can improve convergence speed and solution quality.

Earlier studies introduced a modification of the acceleration coefficients by assigning unequal values ($C_1 = 0.5$ and $C_2 = 2.5$), resulting in improved convergence behavior for certain optimization tasks [9]. In addition, dynamically adjusting the acceleration coefficients at each iteration was reported to enhance the algorithm's capability to obtain the global optimum solution [10]. To address this, several approaches have been introduced using both linear and nonlinear functions to adaptively adjust acceleration coefficients throughout the iterations, including Sigmoid-Based Acceleration Coefficients (SBAC) [8], Nonlinear Dynamics Acceleration Coefficients (NDAC), Time-Varying Acceleration Coefficients (TVAC) [11], and Sine-Cosine Acceleration Coefficients (SCAC) [12]. These modifications allow for adaptive changes in acceleration coefficients during the optimization process, improving PSO's convergence and solution quality. Among these, the Sigmoid-Based Acceleration Coefficients have shown particularly strong performance. In previous studies, this method consistently outperformed others across several benchmark functions and was ranked first overall in final performance evaluations [8]. Despite these promising results, the nature of the sigmoid function still introduces relatively abrupt transitions in acceleration values during iterations, which may affect the stability of the swarm's movement in more complex search landscapes. Recognizing this limitation, this study explores whether a smoother functional form could further enhance the adaptive behavior of PSO.

To this end, this research proposes the use of the hyperbolic tangent (tanh) function as the basis for modifying acceleration coefficients. The smooth and continuous characteristics of the tanh function allow acceleration coefficients to change more gradually across iterations, thereby helping preserve swarm diversity and reducing the risk of premature convergence to local optima [13], [14]. Additionally, the inherent properties of tanh, which map input values to an output range of -1 to 1, help prevent excessive particle velocity updates, thereby maintaining stability throughout the optimization process [11].

This study introduces a modification to the PSO hyperparameters by defining the acceleration coefficients (C_1 and C_2) using a hyperbolic tangent (tanh)-based scheme. The effectiveness of the proposed hyperparameter modification in achieving convergence of the modified PSO algorithm will be evaluated using the convergence criteria theorem from [5]. To evaluate the effectiveness of the proposed PSO modification, comparisons will be made with several existing approaches, including SBAC-PSO, NDAC-PSO, TVAC-PSO, SCAC-PSO. Performance evaluation will be conducted using benchmark unimodal and multimodal functions to assess the method's effectiveness under different optimization scenarios and to provide a more thorough numerical analysis. The assessment considers important performance indicators, including the mean and standard deviation of the obtained best solutions from several independent runs. Unimodal functions are used to measure how quickly the method reaches the optimal solution in a relatively simple landscape, while multimodal functions are used to assess its capability to avoid local optima within more complex search environments.

Furthermore, this study will also investigate the influence of parameters within the tanh function on the solution search dynamics of PSO to understand the extent to which the tanh function can adapt to the characteristics of different optimization problems. Through this approach, deeper insights into the acceleration mechanism in PSO can be obtained, along with recommendations for optimal hyperparameter tuning across various optimization problem types. Additionally, this study can serve as a reference for researchers and developers of swarm intelligence-based optimization algorithms in addressing challenges related to convergence and solution exploration more effectively.

2. Methods

Based on the limitations discussed in the previous section, This study introduces a modified Particle Swarm Optimization (PSO) algorithm by incorporating a hyperbolic tangent (tanh)-based approach for adjusting the acceleration coefficients. The objective of this modification is to enhance the convergence performance of PSO by achieving a better balance between exploration and exploitation throughout the optimization process. Before evaluating the performance of this proposed modification, it is important to first examine the mathematical convergence criteria for PSO and how these criteria are associated with parameter configurations, including the acceleration coefficients (C_1 and C_2) and inertia weight (ω).

The methodology section describes the analytical approaches utilized in this study in a sequential manner, as presented in Figure 1. This includes the analysis of PSO convergence criteria, formulation of the proposed tanh-based modification, experimental design using benchmark functions, and performance comparison with other acceleration coefficient strategies.

2.1 Analysis of Convergence Criteria for PSO Parameters

Particle Swarm Optimization (PSO) was initially introduced by [15] as an algorithm for optimizing its continuous nonlinear functions.

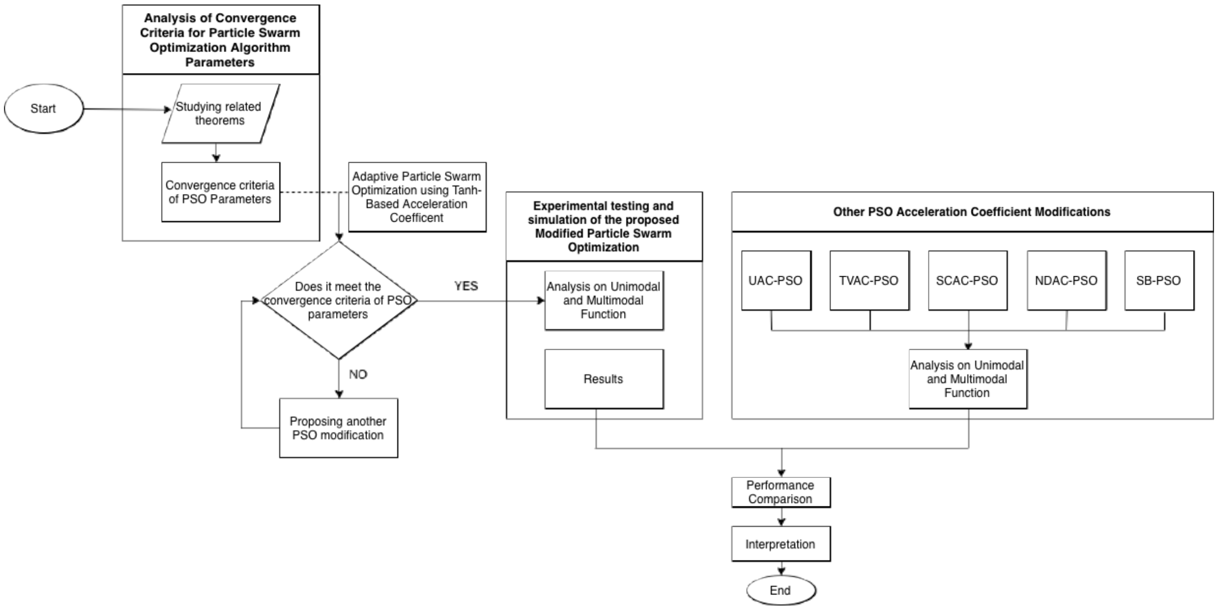

Figure 1. Flowchart of the research

In PSO, each particle independently searches for its best position (Pbest) while incorporating the optimal position identified by the entire swarm (Gbest). This allows the algorithm to converge toward an optimal solution. Each particle shares information about its best position with other particles and adjusts its position and velocity accordingly based on the received information. This indicates that the position and velocity of each particle are iteratively adjusted throughout the search process. The iteration stops when a stopping criterion is met, or when the convergence value is achieved. The position and velocity of each particle are updated according to Equations 1 and 2.

$$x_i^{(t+1)} = v_i^{(t+1)} + x_i^{(t)} \quad (1)$$

$$v_i^{(t+1)} = \omega\, v_i^{(t)} + c_1 r_1 \left(p_{(i,lb)}^{(t)} - x_i^{(t)}\right) + c_2 r_2 (p_{gb}^{(t)} - x_i^{(t)}) \quad (2)$$

$x_i^{(t+1)}$ is the position of particle i at iteration t+1; $v_i^{(t+1)}$ represents the velocity of particle i at iteration t+1; $x_i^{(t)}$ represents the position of particle i at iteration t; $v_i^{(t)}$ represents the velocity of particle i at iteration t; c_1 and c_2 represent the acceleration coefficients, which are assigned a value of 2 in the standard PSO algorithm; ω is the inertia weight; $p_{(i,lb)}^{(t)}$ is the personal best position; r_1 and r_2 are random values [0,1]; $p_{gb}^{(t)}$ is the gbest.

The original PSO algorithm has several drawbacks, as highlighted by studies such as [6], [7]. These studies demonstrate that PSO particles may experience premature convergence toward a stable state, causing the search process to become trapped in local optimal solutions. Furthermore, PSO convergence has been found to be influenced by the proper balance between exploration and exploitation capabilities, allowing particles to effectively approach the global optimal solution [16].

The following theorem presents an analysis of the convergence behavior of PSO toward the global optimal solution.

Theorem 1. A particle in the Particle Swarm Optimization (PSO) algorithm has been proven to converge toward a stable point given by $\frac{c_1 p_{(i,lb)}^{(t)} + c_2 p_{gb}^{(t)}}{c_1 + c_2}$, provided that $\max\{|\lambda_1|, |\lambda_2|\} < 1$ where λ_1 and λ_2 represent the eigenvalues that characterize the dynamic behavior of a basic PSO system with an inertia weight(ω) [5] .

Based on this theorem, if ω, c_1, c_2 are chosen in such a way: $\frac{c_1+c_2}{2} - 1 < \omega$ and $0 < c_1 + c_2$ that the condition $max\{||\lambda_1||, ||\lambda_2||\} < 1$ is satisfied, then the system guarantees convergence to the stable point. It can be seen that the parameter settings used in the original PSO, namely $c_1 = c_2 = 2$, and $w = 1$ do not fulfill the convergence conditions required for PSO parameters. This occurs because $c_1 + c_2 = 2 + 2 = 4 > 0$ and $\frac{c_1+c_2}{2} - 1 = \frac{2+2}{2} - 1 = 1 = w$. These conditions indicate that the original PSO formulation may generate a divergent particle trajectory [17]. Consequently, this issue creates limitations in applying the original PSO to practical optimization problems. The divergence of particle trajectories indicates that the standard PSO may not consistently achieve satisfactory convergence performance. To overcome this limitation, this study investigates the modification of acceleration coefficients to establish a more effective balance between exploration and exploitation capabilities. At this stage, we will examine whether the proposed tanh-based acceleration coefficient modification for PSO, as shown below, satisfies the PSO convergence criteria stated in Theorem 2.1. Specifically, we aim to verify whether $max\{||\lambda_1||, ||\lambda_2||\} < 1$ ensuring that the particle search process toward personal best and global best is guaranteed to achieve convergence.

2.2 Performance Assessment and Simulation Analysis of the Proposed TANH-PSO

This study also conducts an empirical analysis through a set of experimental evaluations to assess the performance of the proposed acceleration coefficient modification. The experiments are conducted by implementing the modified PSO algorithm on a set of standard benchmark optimization functions. Testing is performed using two main categories of objective functions: unimodal functions and multimodal functions. The selected functions are intended to evaluate the convergence performance and effectiveness of the proposed method in obtaining optimal solutions under various optimization conditions.

Unimodal functions are optimization functions that contain only one global optimum, making them appropriate for analyzing the convergence speed of an algorithm. In this regard, an algorithm with higher efficiency is expected to achieve the optimal solution within fewer iterations. The Sphere Function using Equation 3.

$$\min\ f_1(x) = \sum_{i=1}^{n} x_i^2 \tag{3}$$

The global optimal solution is positioned at $x^* = 0$ with $f(x^*) = 0$, and the search space is bounded by $-10 \le x_i \le 10$.The Schwefel Function using Equations 4.

$$\min\ f_2(x) = \sum_{i=1}^{n} |\, x_i\, | + \prod_{i=1}^{n} |\, x_i\, | \tag{4}$$

where The global optimal solution is positioned at $x^* = 0$ with $f(x^*) = 0$, and the search space is bounded by $-100 \le x_i \le 100$.The Rosenbrock Function using Equation 5.

$$\min f_3(x) = \sum_{i=1}^{n} [100\ (x_i^2 - x_{i+1})^2 + (x_i - 1)^2] \tag{5}$$

The global optimal solution is positioned at $x^* = (1,1,\ldots,1)$with $f(x^*) = 0$, and the search domain is constrained within the range defined by $-30 \le x_i \le 30$. These benchmark functions are commonly used to evaluate the exploitation ability, convergence characteristics, and solution accuracy of metaheuristic algorithms in unimodal optimization environments.

Multimodal functions have multiple local optima, making them more challenging for optimization algorithms. The primary purpose of this test is to assess the capability of PSO in avoiding local optima and identifying the global optimal solution. The multimodal functions used in this study are the Griewank Function and Ackley Function.The Griewank Function using Equations 6.

$$min\, f_4(x) = \frac{1}{4000} \sum_{i=1}^{n} (x_i)^2 - \prod_{i=1}^{d} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \tag{6}$$

The global optimal solution is positioned at $x^* = 0$with $f(x^*) = 0$, and the search space is bounded by $-600 \le x_i \le 600$.The Ackley Function using Equations 7.

$$min\, f_6(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n} cos(2\pi x_i)\right) + 20 + e \tag{7}$$

The global optimum occurs at $x^* = 0$ with $f(x^*) = 0$, and the search space is bounded by $-600 \le x_i \le 600$. These multimodal benchmark functions are characterized by multiple local optima, making them appropriate for assessing the exploration ability and robustness of optimization algorithms in preventing premature convergence and reaching the global optimum.

2.3. Performance Comparison with Other PSO Acceleration Coefficient Modifications

At this stage, a performance comparison is carried out between the proposed modification of PSO, namely the Tanh-Based Acceleration Coefficient, and several existing PSO variants. The Unbalanced Acceleration Coefficient PSO (UACPSO) was proposed by [6] by modifying the cognitive and social acceleration parameters (C_1 and C_2) to enhance the convergence speed of PSO. In their implementation, the acceleration coefficients were assigned fixed and unbalanced values, with $C_1 = 0.5$and $C_2 = 2.0$. TVAC-PSO, proposed in [9], employs a dynamic adjustment strategy for the cognitive and social coefficients during the optimization process. In this approach, the cognitive coefficient (C_1) gradually decreases, while the social coefficient (C_2) increases as the iteration progresses. The corresponding equations are shown in Equations 8 and 9.

$$C_1 = \left(C_{1f} - C_{1i}\right)\frac{iter}{MAXITR} + C_{1i} \tag{8}$$

$$C_2 = \left(C_{2f} - C_{2i}\right)\frac{iter}{MAXITR} + C_{2i} \tag{9}$$

C_{1f}, C_{1i}, C_{2f}, and $C_{2i}$are predefined constants, $iter$ indicates the current iteration, and $MAXITR$ refers to the predefined maximum number of iterations. Inspired by TVAC-PSO and the work reported in [9], SCAC-PSO utilizes trigonometric functions to control the cognitive and social components throughout the optimization process. The acceleration coefficients are calculated using Equations 10 and 11.

$$C_1 = \partial\ x \sin\left(\left(1 - \frac{iter}{MAXITR}\right) x\ \frac{\pi}{2}\right) + \delta \tag{10}$$

$$C_2 = \partial\ x \cos\left(\left(1 - \frac{iter}{MAXITR}\right) x\ \frac{\pi}{2}\right) + \delta \tag{11}$$

$\alpha$and $\delta$are constants with values $\alpha = 2$and $\delta = 0.5$. NDAC-PSO incorporates nonlinear adjustment strategies for the acceleration coefficients to achieve a more effective balance between exploration and exploitation. The cognitive and social coefficients are updated according to Equations 12 and 13.

$$C_1 = -\left(C_{1f} - C_{1i}\right)\left(\frac{iter}{MAXITR}\right)^2 + C_{1f} \tag{12}$$

$$C_2 = C_{1i}\ x\ \left(1 - \frac{iter}{MAXITR}\right)^2 + C_{1f}\ x\ \frac{iter}{MAXITR} \tag{13}$$

C_{1f} and C_{1i} denote positive constants with values of 2.5 and 0.5, respectively, $iter$ represents the current iteration, and $MAXITR$ indicates the maximum iteration limit. SBAC-PSO utilizes a sigmoid function to generate nonlinear variations of the acceleration coefficients throughout the optimization process. The coefficients are determined using Equations 14 and 15.

$$C_1 = \frac{1}{1+e^{(-\lambda.\frac{iter}{MAXITR})}} + 2(C_{1f} - C_{1i})(\frac{iter}{MAXITR} - 1)^2 \quad (14)$$

$$C_2 = \frac{1}{1+e^{(-\lambda.\frac{iter}{MAXITR})}} + (C_{1f} - C_{1i})(\frac{iter}{MAXITR})^2 \quad (15)$$

λ represents a control parameter that adjusts the sigmoid-based acceleration coefficient, with a value of 0.0001. The parameters C_{1f} and C_{1i} are positive constants assigned values of 2.5 and 0.5, respectively. The terms $iter$ and $MAXITR$ represent the current iteration and the maximum number of iterations. These PSO variants are utilized as comparison methods to assess the performance of the proposed Tanh-Based Acceleration Coefficient based on optimization robustness, solution quality, and convergence speed. The experiments were conducted by applying each method to the unimodal and multimodal benchmark functions described previously. The results generated by each PSO variant were subsequently analyzed to compare their convergence behavior and the stability of the obtained solutions. Through this comparative evaluation, the study aims to identify the capability of the proposed acceleration coefficient modification in enhancing PSO performance across various optimization problems.

3. Results and Discussions

Although the proposed tanh-based approach is designed to enhance the balance between exploration and exploitation, adjustments to PSO parameters must also maintain the convergence characteristics of the algorithm. Therefore, the next subsection analyzes the convergence conditions of the proposed approach to ensure that the resulting particle dynamics remain stable.

3.1 Tanh-Based Acceleration Coefficient

The performance of PSO is strongly influenced by its ability to maintain an appropriate balance between exploration and exploitation. Therefore, the right ratio between these two aspects must be carefully established. In general, PSO is expected to initially emphasize exploration to investigate a broad search space and progressively increase exploitation to improve the accuracy of the obtained optimal solution.

Based on this principle, various time-varying strategies have been developed to adjust PSO parameters, including the acceleration coefficients C_1 and C_2. As previously discussed, C_1 influences local exploration tendencies, while C_2 determines the level of global exploitation. Therefore, adaptive adjustment of these coefficients plays an important role in enhancing the balance between exploration and exploitation in PSO.

In this study, the proposed modification of the acceleration coefficients in PSO based on the tanh function is defined as Equations 16 and 17.

$$c_1(iter) = 0{,}5.\left(\tanh\left(2.\left(c_{1f} - c_{1i}\right).\left(\frac{iter\,max - iter}{iter\,max} - 0{,}5\right)\right) + 1\right).\left(c_{1f} - c_{1i}\right) + c_{1i} \quad (16)$$

$$c_2(iter) = 0{,}5.\left(\tanh\left(2.\left(c_{2f} - c_{2i}\right).\left(\frac{iter}{iter\,max} - 0{,}5\right)\right) + 1\right).\left(c_{2f} - c_{2i}\right) + c_{2i} \quad (17)$$

c_{1f}, c_{2f}, c_{1i}, and c_{2i} are positive constant coefficients, with (c_{1f} and $c_{2f} = 2{,}5$; c_{1i} and $c_{2i} = 0{,}5$). The term "iter" denotes the current iteration during the search process [18] , while 'iter max' refers to the maximum iteration count.

Figure 2 visualizes the plot of equations (16) and (17). The value of c_1 gradually decreases per iteration, ranging from 2.5 to 0.5, represented by the blue line. Meanwhile, the value c_2 increases per iteration, ranging from 0.5 to 2.5, shown by the yellow line.

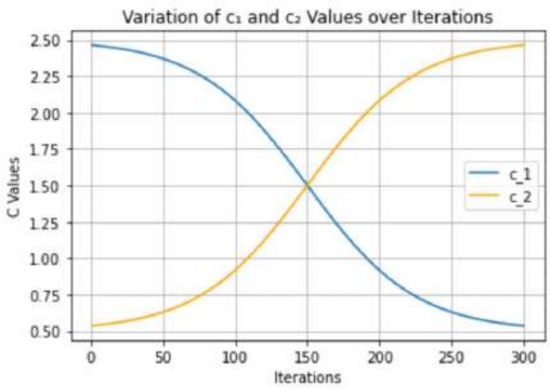

Figure 2. Visualization of c_1 and c_2 Values per Iteration

The proposed approach facilitates a gradual transition between the exploration and exploitation phases. In the initial phase of the search process, c_1 is assigned a relatively high value to encourage particles to perform broader exploration of the search space. Conversely, c_2 begins with a lower value, preventing premature exploitation. As the iterations progress, c_1 gradually decreases while c_2 increases [18]. This dynamic adjustment is designed to create a nonlinear and more natural transition from exploration to exploitation compared to linear-based approaches.

*3.2 Convergence Analysis of Tanh-Based Acceleration Coefficients in Particle Swarm Optimiz*ation

As discussed earlier, the conditions required for each particle in PSO to converge to a stable point have been analyzed. Based on the proposed modification, the values obtained are $c_1 = 0{,}5$; $c_2 = 2{,}5$; w = 0.7298 [19], considering that c_1 and c_2 represent the upper bounds of φ_1 and φ_2. These values were verified using Theorem 1. The results demonstrate that the selected parameter values fulfill the convergence requirements of PSO, as they satisfy the specified conditions $c_1 + c_2 = 0,5 + 2,5 = 3,5 > 0$ and $\frac{c_1+c_2}{2} - 1 = \frac{0,5+2,5}{2} - 1 = 1,5 - 1 = 0,5 < 0,7298$.

Further explanation can be obtained by calculating the value of $\max\{\|\lambda_1\|, \|\lambda_2\|\}$ using the equations for λ_1 and λ_2. As previously discussed, considering the stochastic components with $\varphi_1 = c_1 r_1$ and $\varphi_2 = c_2 r_2$, where $r_1, r_2 \sim U(0,1)$, it is evident that $0 < \varphi_1 + \varphi_2 < 3$ when $c_1 = 0,5$; $c_2 = 2,5$. Next, by substituting $\varphi = \varphi_1 + \varphi_2$ into the equations for λ_1 and λ_2, two sets of calculations are obtained: one for real values of γ and one for complex values of γ. Consider the case where γ is $\mathbb{R}$, when $\varphi \in [0;\ 0,021233349266117]$as shown in Equation 18.

$$max\ \{\|\lambda_1\|, \|\lambda_2\|\} \approx \frac{1,7298-\varphi \pm \sqrt{\varphi^2 - 3,4596\varphi + 0,073}}{4} \quad (18)$$

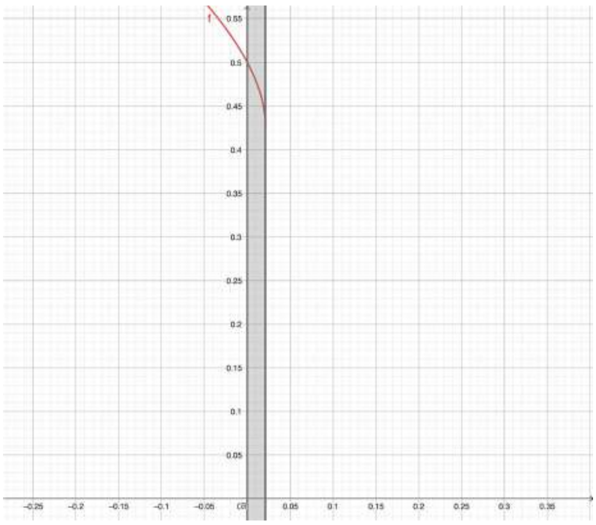

Figure 3a. Graphical Visualization of $\|\lambda_1\|$ and $\|\lambda_1\|$ for $\gamma \in \mathbb{R}$ (Positive Case)

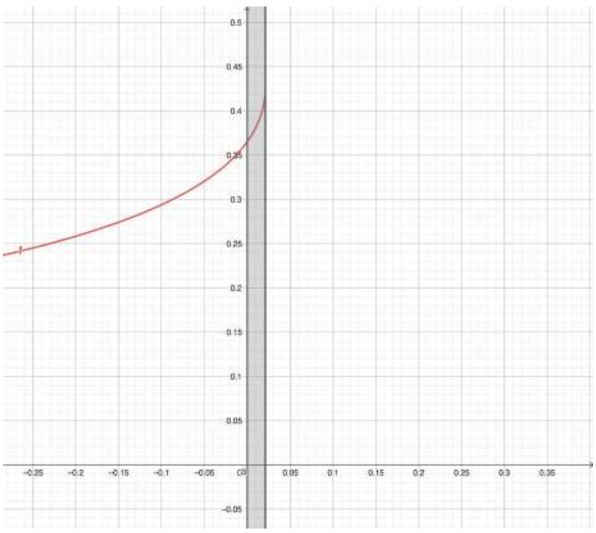

Figure 3b. Graphical Visualization of $\|\lambda_1\|$ and $\|\lambda_1\|$ for Real $\gamma \in \mathbb{R}$ (Negative Case)

Figures 3a and 3b illustrate the solution set for $\|\lambda_1\|$ and $\|\lambda_1\|$ when $\gamma \in \mathbb{R}$. The red line in Figure 3a represents the function: $\max\{\|\lambda_1\|, \|\lambda_2\|\} \approx \frac{1,7298-\varphi+\sqrt{\varphi^2-3,4596\varphi+0,073}}{4}$, Within the range $\varphi \in [0;\ 0,021233349266117]$, the value of $\max\{\|\lambda_1\|, \|\lambda_2\|\}$ remains below 0.5, indicating that the convergence requirements of PSO are satisfied, which requires $\max\{\|\lambda_1\|, \|\lambda_2\|b\} < 1$. Similarly, the red line in Figure 3b represents the function: $\max\{\|\lambda_1\|, \|\lambda_2\|\} \approx \frac{1,7298-\varphi-\sqrt{\varphi^2-3,4596\varphi+0,073}}{4}$, Within the range $\varphi \in [0;\ 0,021233349266117]$, the value of $\max\{\|\lambda_1\|, \|\lambda_2\|\}$ also remains below 0.5, further confirming that the proposed modification satisfies the convergence criteria for PSO. Now, Consider the case where γ is $\mathbb{C}$, when $\varphi \in (0,021233349266117; 3]$as shown in Equation 19.

$$\|\lambda_1\| = \|\lambda_2\| = \sqrt{\frac{(1,7298-\varphi)^2}{4} + \frac{-\varphi^2+3,4596\varphi-0,073}{4}} \approx 0,8542845 \quad (19)$$

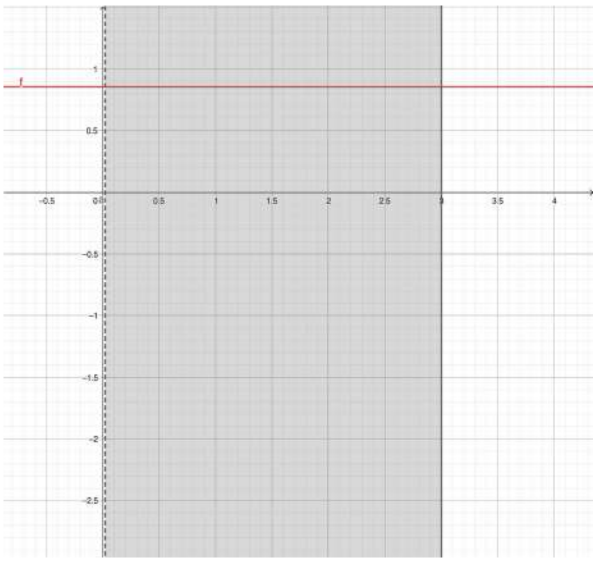

Figure 4. Graphical Visualization of $\|\lambda_1\|$ and $\|\lambda_1\|$ for $\gamma \in \mathbb{C}$

Figure 4 illustrates the solution set for $\|\lambda_1\|$ and $\|\lambda_2\|$ when $\gamma \in \mathbb{C}$. The red line shown in Figure 4 represents the function have been described in Equation (19).

$$\max\{\|\lambda_1\|, \|\lambda_2\|\} \approx \sqrt{\frac{(1,7298-\varphi)^2}{4} + \frac{-\varphi^2+3,4596\varphi-0,073}{4}} \quad (19)$$

Within the range $\varphi \in (0,021233349266117; 3]$, the value of $\max\{\|\lambda_1\|, \|\lambda_2\|\}$ is approximately 0.8542845, which satisfies the convergence criterion of PSO, as it remains below the condition $\max\{\|\lambda_1\|, \|\lambda_2\|\} < 1$. Thus, it can be observed that the proposed modification ensures the generation of a convergent trajectory.

3.3 Analysis and Discussion of Experimental Results

To assess the effectiveness of the proposed TBPSO, a series of experiments were performed using a collection of widely recognized benchmark functions in Table 1, covering six global optimization problems. These six functions have been described in the equations (3)-(7). Figure 5 presents the two-dimensional visualization of the five benchmark test functions used. Table 1 provides the mathematical formulas, number of dimensions, search space boundaries, global optimum values, and the characteristics of each function. This section focuses on analyzing the impact of different acceleration coefficients in the PSO algorithm. The implementation of other methods, such as UACPSO, TVAC-PSO (eq. 8 and 9), SCAC-PSO (eq. 10 and 11), NDAC-PSO (eq.12 and 13), and SB-PSO (eq. 14 dan 15), follows a similar procedure to TBPSO, with the main difference lying in the use of different acceleration coefficients.

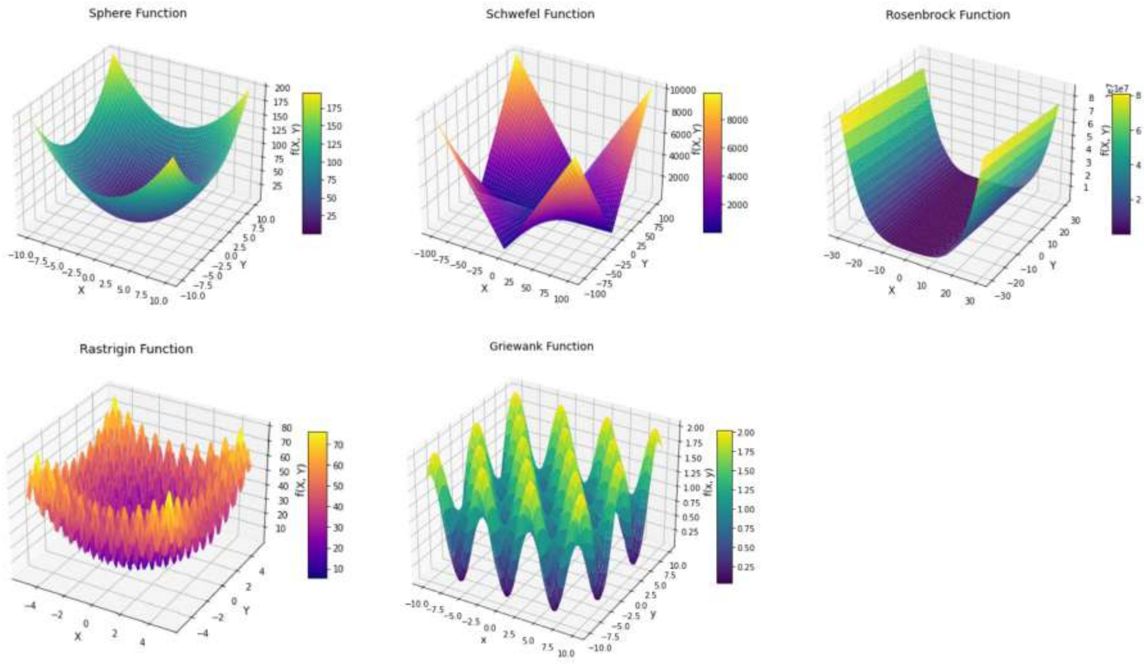

Figure 5. The two-dimensional visualization of the Five Benchmark Test Functions

Table 1. Properties of the Test Function

Test Functions	Dimensions	Search Range	Global Optimum	Properties
Sphere (f1)	10/30	[-10,10]^D	0	Unimodal
Schwefel (f2)	10/30	[-100,100]^D	0	Unimodal
Rosenbrock (f3)	10/30	[-30,30]^D	0	Unimodal
Griewank (f4)	10/30	[-600,600]^D	0	Multimodal
Ackley (f5)	10/30	[-32,32]^D	0	Multimodal

The implementation of other methods, such as UACPSO, TVAC-PSO, SCAC-PSO, NDAC-PSO, and SB-PSO, follows a similar procedure to TBPSO, with the main difference lying in the use of different acceleration coefficients.

The experimental configuration used in this study is established as follows: the swarm population size is set to N = 40 [20], and each benchmark function is independently evaluated through 30 runs, where each run performs 1000 iterations. All PSO algorithms are terminated after reaching the predefined maximum iteration limit to ensure a consistent comparison among different methods and to manage computational resources, as unlimited execution may lead to excessive runtime without guaranteeing significant improvement in solution quality, as commonly practiced in heuristic optimization studies [21]. The performance of TB-PSO is evaluated using several commonly adopted optimization metrics, including the best solution, average solution, and standard deviation. The best solution represents the lowest (or highest, depending on the problem) objective function value achieved across all runs. The average solution provides insight into the algorithm's general performance over multiple runs, which is important because metaheuristic algorithms like PSO are stochastic [22] in nature and may yield different results in each execution. By observing the average, we can assess whether the algorithm consistently finds good solutions or only performs well occasionally. The standard deviation, on the other hand, indicates the stability or robustness of the algorithm [23]. A low standard deviation means the results are tightly clustered around the average, suggesting the algorithm performs reliably across runs. A high standard deviation implies high variability, which may indicate sensitivity to initial conditions or instability in convergence. These metrics assess the effectiveness of TB-PSO in solving unimodal and multimodal benchmark functions compared to other PSO methods, particularly in terms of result stability.

To further evaluate the advantages of the proposed PSO modification in this study, TB-PSO is compared with five other PSO variants (UAPSO, TVAC-PSO, SCAC-PSO, NDAC-PSO, SB-PSO). It should be noted that the dimensionality of all benchmark functions is configured at 10 and 30 dimensions. The performance evaluation is based on the average best solution (Avg.) and the standard deviation of the best solution (Std.), where the superior results are emphasized in bold.

From the results obtained for function dimensions of 10 on Table 2, it can be observed that although TB-PSO ranks fourth in terms of Avg. for f_1, it secures the top rank twice for f_3 and f_5. For f_2, it ranks second, with a minimal difference compared to TVAC-PSO, which holds the first position. Similarly, for f_4, TB-PSO ranks third, with a slight difference compared to NDAC-PSO in first place and SB-PSO in second. Overall, TB-PSO obtains the highest ranking among all evaluated methods, demonstrating its superior performance based on the average best solution and standard deviation metrics.

Table 2. Results of TB-PSO with different acceleration coefficients under D=10

Function	Item	UACPSO	TVAC-PSO	SCAC-PSO	NDAC-PSO	SAC-PSO	TB-PSO
f_1	Avg.	3.538e-39	9.9284e-45	1.5785e-20	4.6945e-65	5.8679e-73	3.3224e-43
	Std.	8.428e-39	3.9978e-44	5.4567e-20	9.2316e-65	1.4079e-72	8.6482e-43
	Rank	5	3	6	2	1	4
f_2	Avg.	103.3333	4.0695e-21	7.3839e-09	4.8592e-08	2.1391	4.8640e-20
	Std.	87.4960	1.5557e-20	1.6545e-08	2.6168e-07	0.0001	8.7043e-20
	Rank	6	1	3	4	5	2
f_3	Avg.	15644.57	2.3721	4.5008	7.2407	6.9532	1.6594
	Std.	33273.91	3.0931	2.5277	18.6422	11.1224	1.4737
	Rank	6	2	3	5	4	1
f_4	Avg.	0.1311	0.0565	0.0695	0.0416	0.0482	0.0542
	Std.	0.0675	0.0307	0.0355	0.0258	0.0313	0.0273
	Rank	6	4	5	1	2	3
f_5	Avg.	0.0385	4.1152	5.4052	4.2337	5.6547	4.70e-15
	Std.	0.2074	6.3773	4.0718	8.8620	1.7724	1.42e-15
	Rank	2	3	5	4	6	1
Avg rank		5	2.6	4.4	3.2	3.6	2.2
Final rank		6	2	5	3	4	1

Table 3. Results of TB-PSO with different acceleration coefficients under D=30

Function	Item	UACPSO	TVAC-PSO	SCAC-PSO	NDAC-PSO	SAC-PSO	TB-PSO
f_1	Avg.	60.00	0.0007	3.0866e-05	1.3887	0.5386	0.0165
	Std.	75.7188	0.0019	4.5051e-05	0.8974	0.5100	0.0349
	Rank	6	2	1	5	4	3
f_2	Avg.	620.2326	10.0128	34.0329	121.5802	112.7581	0.0748
	Std.	285.9189	39.5781	59.1743	57.5216	80.2891	0.1778
	Rank	6	2	3	5	4	1
f_3	Avg.	8024586.7	55.1368	132.4436	8637.22	2438.94	132.834
	Std.	23993091.4	45.8024	120.7221	10601.94	11.1224	143.74
	Rank	6	1	2	5	4	3
f_4	Avg.	69.3386	0.1325	0.0209	2.1649	1.4999	0.3633
	Std.	72.5798	0.2176	0.0204	0.8729	0.6209	0.3399
	Rank	6	2	1	5	4	3
f_5	Avg.	14.5509	2.2814	0.0729	5.1091	3.3869	1.8031
	Std.	6.0579	0.6517	0.0592	1.0914	0.8370	0.6055
	Rank	6	3	1	5	4	2
Avg rank		6	2	1.6	5	4	2.4
Final rank		6	2	1	5	4	3

For the 30-dimensional functions on Table 3, TB-PSO ranks first once for f_2. It secures the second position for f_5, just behind SCAC-PSO. Meanwhile, for f_1, f_3, and f_4, TB-PSO ranks third. Although TB-PSO's ranking is not as high in the 30-dimensional case as in the 10-dimensional one, it still demonstrates competitive results compared to other PSO variants. This decline in performance does not imply that TB-PSO is ineffective; rather, it highlights the increased complexity of high-dimensional optimization, which requires broader exploration strategies. Such performance degradation is a well-documented challenge in PSO-based optimization methods, especially in high-dimensional search spaces [24], [25] where premature convergence or loss of diversity often occurs. In comparison, previous studies such as [8] have also reported that their proposed PSO variants showed performance drops when scaling from 10 to 30 dimensions, emphasizing that maintaining a balance between exploration and exploitation becomes more difficult as dimensionality increases.

The key factor influencing TB-PSO's performance is the tanh-based acceleration mechanism, which provides a controlled transition from exploration to exploitation. In lower dimensions, this strategy has proven highly effective in achieving rapid convergence without compromising solution quality. However, in higher dimensions, additional modifications may be required to enhance exploration and prevent convergence to suboptimal solutions. Minor refinements, such as more dynamic parameter adaptation or additional search mechanisms, could further strengthen TB-PSO's capability in handling optimization across different dimensional scenarios. Overall, these findings demonstrate that the proposed TB-PSO modification provides substantial improvements in optimization performance, particularly in lower-dimensional search spaces. With further refinements, the method has the potential to become a more flexible and effective optimization solution, even for high-dimensional problems.

For future research, it is recommended to apply TB-PSO to real-world optimization problems, such as scheduling, energy management, or weather prediction with complex variables. Testing the algorithm in practical situations will help assess how well the tanh-based approach works in dynamic environments and may reveal ways to improve the method so it becomes more adaptive and effective for real-world applications.

4. Conclusions

This study introduces a Tanh-Based Particle Swarm Optimization (TB-PSO) approach that incorporates a hyperbolic tangent (tanh)-based mechanism for adjusting acceleration coefficients to enhance the balance between exploration and exploitation. The continuous and smooth characteristics of the tanh function enable a gradual adjustment of acceleration values throughout iterations, helping to preserve swarm diversity and avoid premature convergence. Moreover, since the tanh function maps inputs to a bounded range of −1 to 1, it prevents excessive velocity updates and contributes to stable convergence behavior. Convergence analysis confirms that TB-PSO satisfies stability criteria, making it suitable for optimization tasks. Experimental results demonstrate that TB-PSO performs particularly well in 10-dimensional benchmark problems, achieving the 1st rank out of 5 PSO variants based on solution quality and stability. In 30-dimensional problems, TB-PSO remains competitive, ranking 3rd out of 5, indicating its adaptability to increased problem complexity, although broader exploration mechanisms are required for higher-dimensional search spaces.In terms of computational complexity, TB-PSO does not introduce significant additional overhead compared to others PSO variants. Furthermore, applying TB-PSO to real-world optimization problems and benchmark datasets would provide deeper insights into its practical effectiveness and scalability.

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