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Hybridizing Particle Swarm Optimization with the Filled Function Method for Enhanced Global Optimization Performance

Kadrah Ali Alsafi [1], Idris A. Abdulhamid [2]*

[1,2] Department of Mathematics, Faculty of Science, University of Omar Almukhar , Albyda, Libya

التهجين بين خوارزمية تحسين سرب الجسيمات وطريقة الدالة المملوءة لتعزيز أداء الامثلية العالمية

خضرة علي الصافي**1**، ادريس عطيه مسعود**2***

2،1 قسم الرياضيات، كلية العلوم، جامعة عمر المختار، البيضاء، ليبيا

*Corresponding author: idris.atea@omu.edu.ly

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Abstract:
This research proposes a novel hybrid optimization algorithm that integrates Particle Swarm Optimization (PSO) with the Filled Function Method (FFM) to address the persistent challenges of premature convergence and local optima entrapment in high-dimensional, multimodal optimization problems. The hybrid PSO–FFM algorithm incorporates a one parameter filled function that dynamically modifies the search landscape when stagnation is detected, enabling systematic escape from deceptive basins while maintaining PSO's exploration-exploitation balance. Experimental evaluation across eight benchmark functions (Sphere, Rosenbrock, Rastrigin, Griewank, Ackley, Schwefel, Zakharov, and Alpine1) demonstrates significant performance improvements, with the hybrid algorithm achieving up to 100% enhancement over standard PSO in several cases. The proposed method offers a robust framework for complex optimization tasks, particularly in engineering and computational applications where traditional metaheuristics struggle with complex search landscapes.

Keywords: Particle Swarm Optimization, Filled Function Method, Hybrid Algorithms, Global Optimization, Metaheuristics, Multimodal Optimization.

الملخص
تقترح هذا البحث خوارزمية تحسين هجينة جديدة تدمج بين خوارزمية **تحسين سرب الجسيمات** (Particle Swarm Optimization – PSO) و**طريقة الدالة المملوءة** (Filled Function Method – FFM) لمعالجة التحديات المستمرة المتمثلة في **التقارب المبكر** والانحصار في **القيم الدنيا المحلية** في مسائل التحسين عالية الأبعاد ومتعددة القمم. تتضمن خوارزمية PSO–FFM الهجينة دالة مملوءة أحادية المعامل تقوم بتعديل فضاء البحث ديناميكياً عند اكتشاف حالة الركود، مما يتيح الخروج المنهجي من الأحواض الخادعة مع الحفاظ على توازن الاستكشاف–الاستغلال الذي تتميز به خوارزمية PSO. أظهرت التقييمات التجريبية عبر ثماني دوال معيارية (Sphere، Rosenbrock، Rastrigin، Griewank، Ackley، Schwefel، Zakharov، و Alpine1) تحسناً ملحوظاً في الأداء، حيث حققت الخوارزمية الهجينة تحسناً وصل إلى **100%** مقارنة بخوارزمية PSO القياسية في عدة حالات. وتوفر الطريقة المقترحة إطاراً قوياً لمعالجة مسائل التحسين المعقدة، لا سيما في التطبيقات الهندسية والحاسوبية التي تواجه فيها الخوارزميات التطورية التقليدية صعوبة في التعامل مع فضاءات البحث المعقدة.

الكلمات المفتاحية: تحسين سرب الجسيمات، طريقة الدالة المملوءة، الخوارزميات الهجينة، الامثلية العالمية، الخوارزميات التقريبية (الميتا-استدلالية)، التحسين متعدد القمم.

1. Introduction

Optimization techniques play a critical role in engineering, scientific computing, and decision-making processes, providing systematic approaches for identifying optimal solutions under specified constraints. Among metaheuristic methods, Particle Swarm Optimization (PSO) has emerged as a prominent approach due to its conceptual simplicity, adaptability, and effective balance between exploration and exploitation. Inspired by collective behaviors in biological systems, PSO employs a population of particles that iteratively adjust their positions based on individual and collective knowledge, making it particularly suitable for continuous, nonlinear optimization problems.

Despite its advantages, standard PSO exhibits notable limitations when applied to complex optimization scenarios, particularly those characterized by high dimensionality, multimodality, or deceptive objective functions. The algorithm is prone to premature convergence, stagnation in local optima, and reduced effectiveness as problem complexity increases. These challenges stem from PSO's inherent difficulty in maintaining population diversity and its sensitivity to parameter settings, especially in rugged search landscapes where the global optimum may be separated by numerous local optima.

To address these limitations, this paper introduces a novel hybridization approach that combines PSO with the Filled Function Method (FFM), a deterministic technique designed specifically for escaping local optima. The resulting PSO–FFM algorithm integrates the global search capabilities of PSO with the landscape modification properties of FFM, creating a synergistic optimization framework that enhances both exploration and exploitation capabilities.

1.1. Related Work

Among the most prominent approaches in this context is the hybridization of PSO with Genetic Algorithms (GA). Researchers have proposed different strategies for this hybridization, including reciprocal integration, sequential application, or embedding GA operators within the PSO framework [1, 2, 3]. In 1998, Angeline introduced the first concept of hybridization between algorithms by combining Particle Swarm Optimization (PSO) with Genetic Algorithms (GA). Angeline incorporated the principle of selection by proposing a mechanism to eliminate the least effective solutions—either by discarding them or reinitializing them. This approach aimed to enhance solution quality, achieve better optimization results, and reduce the likelihood of falling into local optima [4].
In 2001, Krink, Lovbjerg, Rasmussen proposed the integration of additional mechanisms– such as Genetic Algorithms (GA)–into the Particle Swarm Optimization (PSO) frame- work. This hybrid model yielded improved solution quality and performance compared to using each algorithm independently [5].
For instance, in 2002 Robinson, J., Sinton, S., Rahmat-Samii combined PSO with GA, where PSO contributed to enhancing the search for promising solutions, while GA improved the accuracy in reaching feasible solutions. This synergy resulted in highly precise and high-quality outcomes [6]. In 2003 Shi, X., Lu, Y., Zhou, C., Lee, H., Lin, W., Liang generated the best particles after several iterations and reinitialized them for the second algorithm, while random generation was employed to fill the remaining population [7].
In 2007, Shelokar et al. proposed the first hybrid algorithm between PSO and ACO, which they called PSACO. PSO generates and processes the initial values, then inputs them to ACO. The algorithm proved its efficiency on non-convex functions and achieved a remarkable balance between exploration and exploitation [8].
In 2009, Kaveh and Talatahari developed a hybrid model of three algorithms, using PSO with negative clustering (PSOPC, ACO, HS). This hybridization was effective in optimizing network structures with discrete variables [9].
In 2010, Niknam and Amiri presented a hybrid model combining adaptive fuzzy PSO with ACO and K-Means. They dynamically guided ACO using Q-Learning [10]. In 2011, Chen et al. proposed a hybrid framework that integrates ACO-PSO with GA and SA, aiming to enhance global search efficiency and improve the quality of solutions [11]. In the same year, Xiong and Wang introduced the Two-stage ACO-
PSO Clustering (TAPC) method, which significantly improved K-Means clustering performance while reducing its sensitivity to random initialization [12].
In 2012, Kiran et al. proposed the HAP model, combining ACO and PSO, starting independently and then influencing each other through optimal solutions [13].

2. Material and methods

2.1 Particle Swarm Optimization Framework

The operational framework of Particle Swarm Optimization (PSO) is centered around a collective intelligence paradigm, wherein a decentralized population of search agents referred to as particles stochastically explores the search space $\mathcal{X} \subseteq \mathbb{R}^d$. Within this iterative process, each individual agent functions as a repository for its own historical peak performance. Formally, a swarm $\mathcal{S}$ is defined as a set of N discrete particles $\{P_1, P_2, \dots, P_N\}$, where the sets $I = \{1,2,\dots,N\}$ and $D = \{1,2,\dots,d\}$ are utilized to index the particles and their corresponding spatial dimensions, respectively.

At each discrete temporal interval t, the dynamic status of an arbitrary particle i is rigorously defined by the following parameters:

$$P_i^{(t)} = \left(\mathbf{x}_i^{(t)}, \mathbf{v}_i^{(t)}, \mathbf{pbest}_i^{(t)}, \mathcal{N}_i^{(t)}\right), \quad \forall i \in I. \tag{1}$$

2.1.1 Position and Velocity Vectors

The position vector $\mathbf{x}_i^{(t)} = (x_{i1}^{(t)}, \dots, x_{id}^{(t)})^\top \in \mathcal{X}$ represents the particle's current location. The velocity vector $\mathbf{v}_i^{(t)} = (v_{i1}^{(t)}, \dots, v_{id}^{(t)})^\top$ functions as a stochastic displacement operator, determining both direction and magnitude of the particle's trajectory.

Each particle maintains a 'personal best' memory $\mathbf{pbest}_i^{(t)}$, representing the position that yielded the minimum objective value throughout its exploration:

$$\mathbf{pbest}_i^{(t)} = arg\ min_{\tau \in \{0,\dots,t\}} f\left(\mathbf{x}_i^{(\tau)}\right). \tag{2}$$

This serves as a cognitive attractor guiding search toward previously identified high-quality regions. PSO incorporates social information through neighborhood topology $\mathcal{N}_i^{(t)} \subseteq I$. The best position within the neighborhood, $\mathbf{lbest}_i^{(t)}$, acts as a social attractor:

$$\mathbf{lbest}_i^{(t)} = arg\ min_{j \in \mathcal{N}_i^{(t)}} f\left(\mathbf{pbest}_j^{(t)}\right). \tag{3}$$

In the global topology configuration ($\mathcal{N}_i^{(t)} = I$ for all particles), social influence is governed by the global best position:

$$\mathbf{gbest}^{(t)} = arg\ min_{j \in I} f\left(\mathbf{pbest}_j^{(t)}\right). \tag{4}$$

2.1.2 Canonical PSO Update Equations

The original PSO algorithm updates particle velocities and positions using the following equations [40]:

$$v_{ij}^{(t+1)} = v_{ij}^{(t)} + c_1 r_{1j}^{(t)}\left(pbest_{ij}^{(t)} - x_{ij}^{(t)}\right) + c_2 r_{2j}^{(t)}\left(gbest_j^{(t)} - x_{ij}^{(t)}\right) \tag{5}$$

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)} \tag{6}$$

where:

- $i \in I$ and $j \in D$ denote particle index and dimension respectively
- $v_{ij}^{(t)}$: velocity of particle i in dimension j at iteration t
- $x_{ij}^{(t)}$: position of particle i in dimension j at iteration t
- $pbest_{ij}^{(t)}$: personal best position of particle i in dimension j
- $gbest_j^{(t)}$: global best position in dimension j
- c_1, c_2: cognitive and social acceleration coefficients
- $r_{1j}^{(t)}, r_{2j}^{(t)} \sim U(0,1)$: independent random variables uniformly distributed in [0,1] for each dimension j and iteration t

Algorithm 1: Canonical Particle Swarm Optimization (PSO)

Input : Objective function $f\ (\boldsymbol{x})$; bounds (lb, ub); dimension d; swarm size N; maximum iterations T; inertia weight w; cognitive and social coefficients c_1, c_2

Output : Global best solution $gbest$

for $i = 1$ **to** N **do**
    Initialize particle position $\boldsymbol{xi} \sim U\ (lb, ub)$
    Initialize particle velocity $\boldsymbol{vi} \sim U\ (-vmax, vmax)$
    Set personal best $pbesti = \boldsymbol{xi}$

Evaluate $f\ (pbesti)$ for all particles
Set $gbest = arg\ mini\ f\ (pbesti)$
for $t = 1$ **to** T **do**
    for $i = 1$ **to** N **do**
        Generate random vectors $\boldsymbol{r}1, \boldsymbol{r}2 \sim U\ (0, 1)^d$
        Update velocity
$$\boldsymbol{vi} \leftarrow w\boldsymbol{vi} + c1\boldsymbol{r}1 \odot (pbesti - \boldsymbol{xi}) + c2\boldsymbol{r}2 \odot (gbest - \boldsymbol{xi})$$
        Update position:
$$\boldsymbol{xi} \leftarrow \boldsymbol{xi} + \boldsymbol{vi}$$
        Apply boundary constraints if necessary

        Evaluate fitness $f\ (\boldsymbol{xi})$
        if $f\ (\boldsymbol{xi}) < f\ (pbesti)$ **then**
            $pbesti \leftarrow \boldsymbol{xi}$

    Update global best: $gbest = arg\ mini\ f\ (pbesti)$

return $gbest$

2.2 Filled Function Method

The Filled Function Method (FFM) is a recent mathematical technique designed to address one of the most difficult challenges in global optimization: escaping local minima while looking for the global optimum of a multivariable function. Traditional optimization algorithms, such as gradient-based methods or Newton and quasi-Newton approaches, are primarily local in nature. They are good at finding a minimum near the initial starting point, but they frequently become stuck in a local optimum, failing to reach the genuine global solution.

2.2.1 Definition of the Filled Function $\boldsymbol{P}(\boldsymbol{x}, \boldsymbol{x}^*)$

A function $\boldsymbol{P}(\boldsymbol{x}, \boldsymbol{x}^*)$is called the filled function of $f(x)$ at the local minimum point x_1^* if $\boldsymbol{P}(\boldsymbol{x}, \boldsymbol{x}^*)$ has the following properties:

- x_1^* is a maximizer of $\boldsymbol{P}(\boldsymbol{x}, \boldsymbol{x}^*)$ and the whole basin B_1^* of $f(x)$ at x_1^* becomes a part of a hill of $\boldsymbol{P}(\boldsymbol{x}, \boldsymbol{x}^*)$;
- $\boldsymbol{P}(\boldsymbol{x}, \boldsymbol{x}^*)$has no minimizers or saddle points in any higher basin of $f(x)$ than B_1^*;
- If $f(x)$ has a lower basin than B_1^*, then there is a point x' in such a basin that minimizes $\boldsymbol{P}(\boldsymbol{x}, \boldsymbol{x}^*)$ on the line through x' and x_1^*.

2.2.2 The Selected Filled Function for Hybridization

In this study, a simplified one-parameter filled function is selected for hybridization with Particle Swarm Optimization (PSO). The choice of this specific filled function is motivated by its balance between simplicity, numerical stability, and strong compatibility with population-based metaheuristic algorithms. While it employs a single control parameter μ, its design minimizes the tuning complexity often associated with earlier multi-parameter versions, which is a crucial advantage when integrating deterministic techniques with stochastic optimization methods such as PSO.

The main idea of the selected filled function is to modify the local landscape of the objective function around the current best solution ($gbest$) in such a way that this point becomes an unattractive region for further search. This is achieved by introducing a distance-based repulsion term combined with a penalization mechanism for worse solutions, regulated by the single parameter μ. As a result, the filled function transforms the basin of attraction of the current $gbest$ into a hill, encouraging the search process to move away from it and explore regions with potentially lower objective values. This one-parameter formulation adapts effectively based on the intrinsic characteristics of the objective function and the chosen μ value, making the method robust and practical for implementation in high-dimensional or multimodal optimization problems.
The one-parameter filled function adopted in this work is defined as follows:

$$F(\mathrm{x}) = -\| \mathrm{x} - gbest \|^2 + \mu \max(0, f(\mathrm{x}) - f(gbest))^3, \tag{7}$$

where $\mathbf{x} \in \mathbb{R}^n$ denotes a candidate solution, $gbest$ represents the current best solution (acting as the local minimizer), $\mu > 0$ is the control parameter, and $\|\cdot\|$ is the Euclidean norm.

3. Hybridization of (PSO-FFM)

The concept of hybrid algorithms emerged in the 1990s, enabling scientists and researchers to merge two or more distinct algorithms into a single, cohesive framework. This integrative approach is designed to solve a given problem in a novel and more effective manner. A primary strength of hybrid algorithms is their capacity to mitigate the shortcomings and overcome the weaknesses of the individual algorithms they comprise. By leveraging the strengths of each component, they achieve enhanced robustness, efficiency, and accuracy in locating optimal solutions [15,19].
A critical feature of these hybrids is their ability to escape local optima, avoiding premature convergence on satisfactory but sub-optimal solutions. Each hybrid model aims to synergistically combine the advantages of its constituent algorithms while circumventing their limitations. Consequently, hybrid algorithms have demonstrated superior numerical performance compared to the standalone use of their components [14,16]. They have proven particularly effective in solving complex problems and optimizing high-dimensional functions, ultimately contributing to reduced computational time and cost while achieving superior results [17-20].

Algorithm 2: Hybrid Particle Swarm Optimization with Filled Function Method (PSO–FFM)

Input : Objective function $f(\boldsymbol{x})$; bounds (lb, ub); dimension d; swarm size N; max iterations T; inertia weight w; acceleration coefficients $c1, c2$; stagnation limit L; filled function parameter μ
Output : Global best solution $gbest$

1 **Initialization:**
- Initialize positions: $\boldsymbol{x}i \sim U(lb, ub)$
- Initialize velocities: $\boldsymbol{v}i \sim U(-0.1, 0.1)$
- Set personal bests: $pbesti = \boldsymbol{x}i$, evaluate $f(pbest_i)$
- Set global best: $gbest = arg\ mini\ f(pbesti)$
- Initialize stagnation counter: $stagnation \leftarrow 0$

2 Filled Function (FFM):

$$F(\boldsymbol{x}) = -\| \boldsymbol{x} - gbest \| 2 + \mu\, max(0, f(\boldsymbol{x}) - f(gbest))3$$

3 **for** $t = 1$ **to** T **do**
4 **for** $i = 1$ **to** N **do**
5 Generate random vectors $\boldsymbol{r}1, \boldsymbol{r}2 \sim U(0,1)d$
6 Update velocity: $\boldsymbol{v}i \leftarrow w\boldsymbol{v}i + c1\boldsymbol{r}1 \odot (pbesti - \boldsymbol{x}i) + c2\boldsymbol{r}2 \odot (gbest - \boldsymbol{x}i)$
7 Update position: $\boldsymbol{x}i \leftarrow \boldsymbol{x}i + \boldsymbol{v}i$
8 Apply boundary constraints and evaluate $f(\mathbf{x}_i)$
9 **if** $f(\boldsymbol{x}i) < f(pbesti)$ **then**
$\boldsymbol{pbesti} \leftarrow \boldsymbol{xi}$
10 Update global best: $gbest \leftarrow arg\ mini\ f(pbesti)$
if $gbest$ *not improved* **then**
$stagnation \leftarrow stagnation + 1$
else
stagnation ← 0
11 **if** $stagnation \geq L$ **then for** $i = 1$ **to** N **do**
12 Generate $\boldsymbol{\epsilon} \sim U(-1,1)d$
13 Update position using FFM: $\mathbf{x}_i \leftarrow \mathbf{x}_i + \boldsymbol{\epsilon} \odot F(\mathbf{x}_i)$ Apply boundary constraints and evaluate $f(\mathbf{x}_i)$

if $f\,(\boldsymbol{xi}) < f\,(pbesti)$ **then**
$\quad pbesti \leftarrow \boldsymbol{xi}$
Update global best again: $gbest \leftarrow arg\ mini\ f\ (pbesti)$
Reset stagnation counter: *stagnation* ← 0
return $gbest$

4. Results and discussion

The experimental evaluation was conducted on a comprehensive set of benchmark functions representing various optimization challenges, including unimodal, multimodal, separable, and non-separable functions. The algorithms were implemented in Python 3.8. Each experiment was repeated 30 times with different random seeds to ensure statistical significance.

Benchmark test functions are widely used in numerical optimization and swarm intelligence literature as standardized and reliable tools for evaluating and comparing the performance of metaheuristic algorithms. These functions provide controlled mathematical environments with diverse landscape characteristics, allowing a systematic assessment of algorithmic behavior in terms of convergence speed, solution accuracy, exploration–exploitation balance, and robustness against premature convergence.

In this paper, a carefully selected set of well-established benchmark test functions is adopted to evaluate the performance of the proposed and comparative optimization algorithms under heterogeneous and increasingly complex search conditions. This selection ensures consistency with existing literature and enables meaningful comparison with previously published results.

1. Sphere Function
The simplest test case. It is smooth, unimodal (one peak/valley), and symmetric.

$$f(x) = \sum_{i=1}^{d} x_i^2$$

- Domain: $[-100{,}100]^d$
- Global Optimum: $f(0) = 0$
- Property: Highly efficient for testing the convergence speed of an algorithm.

2. Rosenbrock Function
Also known as "Rosenbrock's Valley" or the "Banana Function."

$$f(x) = \sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2]$$

- Domain: $[-30, 30]^d$
- Global Optimum: $f(1) = 0$
- Property: The global optimum is inside a long, narrow, parabolic valley. Finding the valley is easy, but converging to the global minimum is notoriously difficult.

3. Rastrigin Function

A highly multimodal function—it's full of local minima (traps) that look like a "bed of nails."

$$f(x) = 10d + \sum_{i=1}^{d} [x_i^2 - 10 \cos(2\pi x_i)]$$

- Domain: $[-5.12{,}5.12]^d$
- Global Optimum: $f(0) = 0$
- Property: Tests an algorithm's ability to escape local optima and find the true global minimum.

4. Griewank Function

Similar to Rastrigin, it has many widespread local minima, but the "ruggedness" changes depending on the scale.

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

- Domain: $[-600,600]^d$
- Global Optimum: $f(0) = 0$
- Property: It is non-separable, meaning the variables are interlinked, making it harder to solve one dimension at a time.

5. Ackley Function

Characterized by a nearly flat outer region and a very deep, narrow hole at the center.

$$f(x) = -20\, exp\left(-0.2\sqrt{\frac{1}{d}\sum x_i^2}\right) - exp\left(\frac{1}{d}\sum cos(2\pi x_i)\right) + 20 + e$$

- Domain: $[-32,32]^d$
- Global Optimum: $f(0) = 0$
- Property: Algorithms that use simple hill-climbing will get stuck in the flat outer regions and never find the "well."

6. Schwefel 2.26 Function

A deceptive function where the second-best local minimum is very far from the global minimum.

$$f(x) = 418.9829d - \sum_{i=1}^{d} x_i\, sin\left(\sqrt{|x_i|}\right)$$

- Domain: $[-500, 500]^d$
- Global Optimum: $f(420.9687, \ldots, 420.9687) \approx -1.25695$
- Property: Highly prone to tricking algorithms into converging in the wrong direction.

7. Zakharov Function

A plate-shaped function with a very shallow slope leading to the minimum.

$$f(x) = \sum x_i^2 + \left(\sum 0.5\, ix_i\right)^2 + \left(\sum 0.5\, ix_i\right)^4$$

- Domain: $[-5,10]^d$
- Global Optimum: $f(0) = 0$
- Property: It contains no local minima, but its narrow ridge makes it difficult for gradient-based methods.

8. Alpine 1 Function

A "wavy" function that uses absolute values and sine waves.

$$f(x) = \sum |x_i sin(x_i) + 0.1x_i|$$

- Domain: $[-10, 10]^d$
- Global Optimum: $f(0) = 0$
- Property: It is non-differentiable at the minimum due to the absolute value, testing how algorithms handle "sharp" points.

This section presents a detailed performance analysis of the proposed hybrid PSO–FFM algorithm in comparison with the standard PSO. The evaluation focuses on analyzing the impact of the filled function mechanism on convergence behavior, solution accuracy, and overall optimization efficiency across a set of benchmark test functions. By examining both quantitative performance metrics and relative improvements, this section aims to highlight the strengths and limitations of the hybrid approach under different optimization scenarios. The analysis is supported by parameter configuration details and numerical results, providing a clear and objective assessment of the proposed algorithm’s effectiveness.

Table 1 presents the parameter settings used for both the standard PSO and the hybrid PSO–FFM algorithms. To ensure a fair comparison, identical values were assigned to the core PSO parameters in both approaches, while additional parameters related to stagnation detection and the filled function mechanism were introduced only in the hybrid model.

Table 1 Algorithm Parameters for Standard PSO and PSO–FFM

Parameter	Standard PSO	PSO–FFM
Population size (N)	30	40
Maximum iterations (T_{max})	200	300
Stagnation limit (S)	–	10
Inertia weight (ω)	0.7	0.7
Cognitive coefficient (c_1)	1.5	1.5
Social coefficient (c_2)	1.5	1.5
Random factors (r_1, r_2)	U (0, 1)	U (0, 1)
Problem dimension (d)	5	5
Search bounds	[−500, 500]	[−500, 500]
Filled Function parameter (μ)	-	30-40

Table 2 Performance Improvement of PSO–FFM over Standard PSO

Function	Standard PSO	PSO–FFM	Improvement (%)
Sphere	5.378×10^{-14}	2.757×10^{-24}	99.99
Rosenbrock	3.968×10^{2}	5.263×10^{-12}	100
Rastrigin	3.980	1.421×10^{-14}	99.99
Griewank	4.680×10^{-2}	1.477×10^{-2}	68.4
Ackley	20.00	20.00	0
Schwefel	2.369×10^{2}	3.553×10^{2}	-50.0
Zakharov	8.797×10^{-2}	5.885×10^{-15}	100
Alpine1	1.184×10^{-5}	1.957×10^{-9}	99.98

Table 2 reports the optimization results obtained for a set of well-known benchmark functions. The results clearly indicate that the proposed PSO–FFM hybrid out- performs the standard PSO in most cases, achieving substantial performance improvements for functions such as Sphere, Rosenbrock, Rastrigin, Zakharov, and Alpine1. These improvements highlight the effectiveness of incorporating the filled function mechanism in enhancing the search process and avoiding premature convergence.

Table 3 summarizes the parameter settings adopted for the standard PSO algorithm. The selected values correspond to the commonly used and widely accepted default parameters reported in the PSO literature. These settings represent the classical configuration of PSO and are known to provide a balanced trade-off between exploration and exploitation in the search process. By employing these conventional parameters, the performance of the standard PSO serves as a reliable baseline for comparison with the proposed hybrid approach.

Table 3: Parameters Used in Standard PSO

Parameter	Value / Description
Swarm Size (N)	30
Max Iterations (T)	300
Inertia Weight (ω)	0.9
Cognitive Coefficient (c_1)	2.0
Social Coefficient (c_2)	2.0
Stagnation Threshold (ϵ)	1×10^{-6}
Swarm Size (N)	30
Max Iterations (T)	300

Table 4 summarizes the general parameter settings of the hybrid PSO–FFM algorithm. Unlike the conventional PSO, these parameters were tuned to support the filled function mechanism and improve search efficiency by balancing exploration and exploitation. This tuning was aimed at achieving better convergence and higher-quality solutions for the benchmark optimization problems.

Table 4: General Parameters Used in Hybrid PSO-FFM Algorithm

Parameter	Value / Description
Swarm Size (N)	40
Max Iterations (T)	400
Stagnation Limit (S)	15
Inertia Weight (ω)	0.8
Cognitive Coefficient (c_1)	1.8
Social Coefficient (c_2)	1.8
Stagnation Threshold (ϵ)	1×10^{-6}
Fraction of Worst Particles (k_{frac})	0.4
Number of Top Particles for Local Search (m)	5
Random Seed	124
Random Factors (r_1, r_2)	Drawn from uniform $U(0, 1)$

Table 5: Performance Comparison: Standard PSO vs. PSO-FFM Enhanced

Function	Standard PSO	PSO-FFM Enhanced	Improvement (%)
Sphere	4.4795×10^{-16}	4.4635×10^{-27}	100.00
Rosenbrock	2.9369×10^{1}	1.6265×10^{-11}	100.00
Rastrigin	1.1798×10^{1}	1.4211×10^{-14}	100.00
Griewank	9.7488×10^{-2}	1.1779×10^{-13}	100.00
Ackley	2.6789	1.8173×10^{-8}	99.99
Schwefel	2.0752×10^{3}	2.0752×10^{3}	0.00
Zakharov	1.4903	6.7419×10^{-16}	100.00
Alpine1	2.1603×10^{-1}	1.6710×10^{-9}	99.99

Table 5 provides a detailed comparison between the standard PSO and the enhanced PSO–FFM algorithm across a set of benchmark optimization functions. Overall, the results indicate that incorporating the filled function mechanism leads to a substantial improvement in solution quality and convergence accuracy for the majority of the tested functions. The enhanced PSO–FFM consistently achieves values that are several orders of magnitude closer to the known global optima compared to the standard PSO, highlighting the effectiveness of the proposed modification.

For smooth and unimodal functions such as Sphere and Zakharov, the improvement is particularly pronounced. In these cases, the adaptive adjustment of the filled function parameter μ introduces a mild but sufficient perturbation that prevents premature stagnation without disrupting the exploitation process. As a result, the swarm con- verges more precisely toward the global optimum, achieving near-zero objective values with significantly higher numerical accuracy than the standard PSO.

Highly multimodal functions, including Rastrigin, Griewank, and Alpine1, also exhibit remarkable performance gains. These functions are characterized by a large number of local minima that commonly trap conventional swarm-based algorithms. By appropriately increasing the value of μ, the filled function mechanism amplifies the repulsive effect around inferior local optima, enabling particles to escape deceptive regions of the search space. This behavior enhances global exploration and leads to more reliable convergence toward the global optimum, as reflected by the dramatic reduction in final objective values.

The Ackley function shows a notable but comparatively moderate improvement. Although Ackley is multimodal, its global structure is relatively regular and symmetric, allowing the standard PSO to locate competitive solutions. In this case, the filled function mechanism, guided by a moderate value of μ, provides additional refinement rather than a fundamental

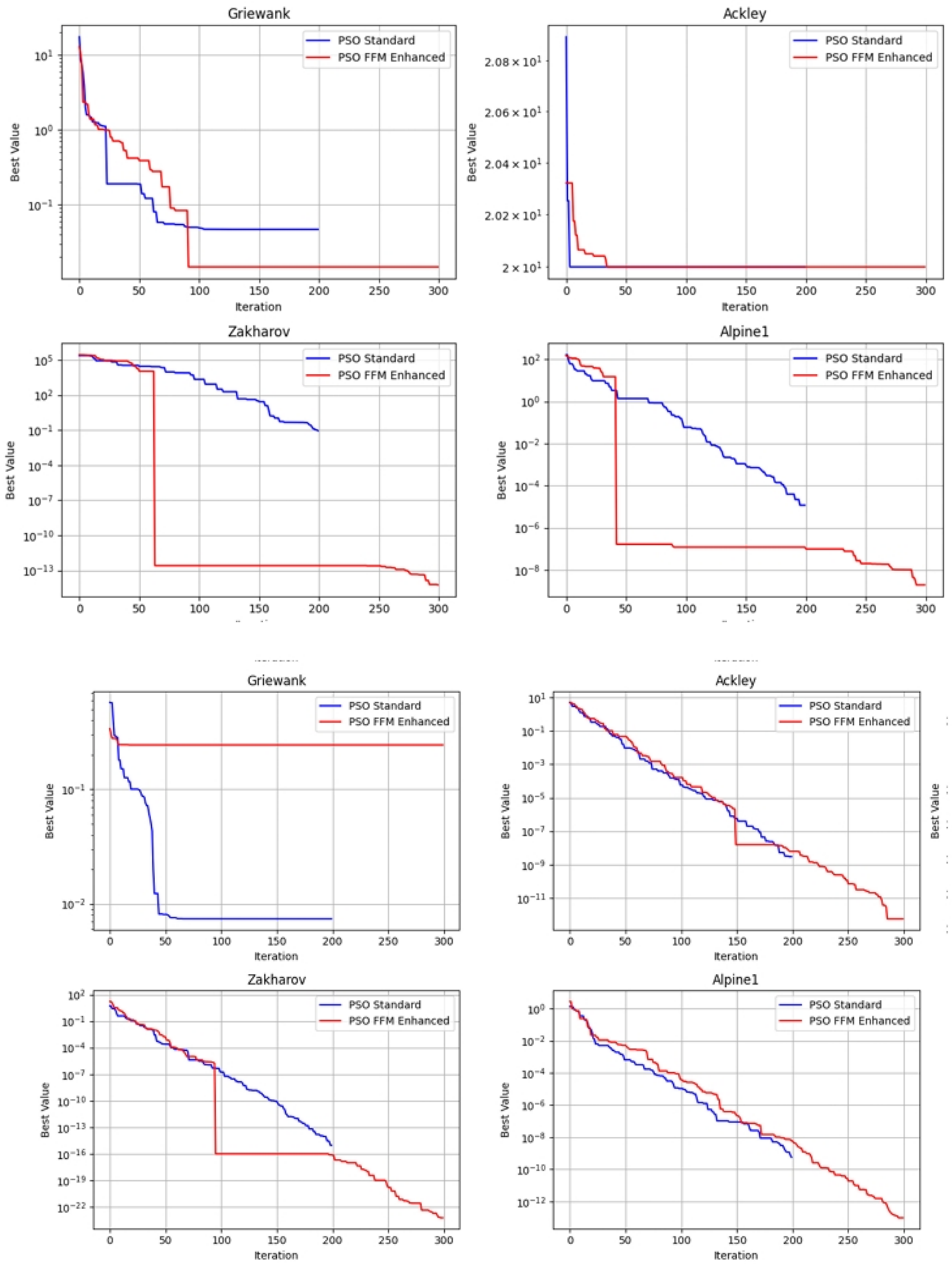

Figure 1: Convergence curves of standard PSO and PSO–FFM across multiple benchmark functions, showing faster descent and lower final values for the hybrid algorithm. change in search behavior, resulting in incremental accuracy gains rather than a complete transformation of performance.

In contrast, no observable improvement is achieved for the Schwefel function, where both algorithms converge to similar objective values. The Schwefel function is known for its highly deceptive landscape, characterized by numerous deep local minima dis- tributed far from the global optimum. In this scenario, the increased exploratory pressure induced by larger values of μ may cause particles to oscillate between distant regions of the search space, preventing stable convergence. This outcome suggests that, for extremely deceptive landscapes, the filled function mechanism may require further adaptation or a more sophisticated control strategy to avoid excessive exploration.

Overall, the observed results demonstrate that the effectiveness of the PSO–FFM enhancement is strongly influenced by the interaction between the filled function parameter μ and the underlying characteristics of the optimization landscape. Proper tuning of μ significantly improves convergence behavior and solution precision for a wide range of functions, while highlighting the limitations of the approach for highly deceptive problems. These findings confirm that the proposed enhancement provides a robust and effective improvement over standard PSO, particularly for unimodal and moderately to highly multimodal optimization problems.

5. Conclusion

This study proposed a hybrid Particle Swarm Optimization framework that combines systematic parameter tuning with the Filled Function Method to address key limitations of conventional PSO, particularly premature convergence and entrapment in local optima. Experimental results on a comprehensive set of benchmark functions demonstrate that the proposed approach consistently outperforms standard PSO in terms of convergence speed, solution accuracy, and robustness, especially for multimodal and high-dimensional problems.

The findings confirm that integrating well-calibrated parameters with complementary mechanisms significantly enhances the exploration–exploitation balance of swarm-based optimization. The proposed PSO–FFM framework offers a reliable and scalable optimization strategy and provides a foundation for future extensions to adaptive, constrained, and multi-objective optimization problems.

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