Enhancing Soil Monitoring and Precision Farming with a Hybrid Ant Lion Optimizer and Particle Swarm Optimization Approach

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Abstract
Artificial Intelligence (AI) solutions in agriculture have emerged as a promising approach to enhance crop management practices and improve yield outcomes. Agriculture is a cornerstone of society, essential for sustenance, economic growth, and tackling global hunger and malnutrition challenges. Algorithms for optimization are crucial for solving complex numerical problems in many scientific and technical domains. In local and global search, respectively. This paper elucidates the transformative impact of AI like the various algorithm and advance IoT on agricultural practices. It also evaluates need of AI in parameter of agriculture. Mainly we focused on soil monitoring using AI technology. AI plays a crucial role in modern farming by analysing real-time soil data from IoT sensors, enabling predictive insights on soil properties. This study proposes a Hybrid Ant Lion Optimizer (ALO) and Particle Swarm Optimization (PSO) approach to improve AI-based soil analysis and agricultural precision. ALO prevents premature convergence during global exploration while excelling in ALO and local exploitations are enhanced by PSO, guaranteeing accurate and faster convergence. Subsequently, the hybrid model combines these algorithms to optimize soil health assessment's key parameters like nutrient levels, moisture content, and crop use along with remote UAV/drone sensing data.
Keywords Soil Monitoring, UAV-based Sensing, Agriculture, Ant Lion Optimizer, Particle Swarm Optimization**:**

1. Introduction

Traditional farming is characterized by reliance on manual labour, a focus on diverse crop rotation, simple tools like ploughs pulled by bullocks, organic fertilizers like cow dung manure, with minimal use of chemical pesticides and fertilizers, making it a relatively sustainable practice, though often with lower yields compared to modern methods. Day by day our world population is growing which majorly effect on food. By doing farming with traditional way requires more man power, efforts. Plowing & tilling manually using bullocks. Applying **Artificial Intelligence (AI)** in farming can transform traditional agricultural practices by improving efficiency, productivity, and sustainability. **Soil monitoring** is correspondingly important for precision agriculture, where farmers analyse data from measurements of soil moisture, nutrients, and pH to manage their activities and decisions more efficiently. Traditional soil monitoring techniques were high cost, time consuming and inefficient. In recent years metaheuristic algorithms have been used as primary techniques for obtaining the optimal solutions of real engineering design optimization problems. **Metaheuristic Algorithms** have good techniques to solve complex, nonlinear problems. Ant Lion Optimizer and Particle Swarm Optimization are two generally used nature-based optimization algorithms known for their effectiveness in global and local search capabilities, respectively. This research enhanced soil monitoring and AI based farming.

1.1 Real-Time Soil Monitoring

- **IoT Integration**: Advanced sensors continuously track soil moisture, pH,

DOI: https://doi.org/10.5281/zenodo.17452079

nutrient levels, and temperature, providing farmers with actionable data (Mane et al., 2025).

- **Data Accessibility**: Farmers can access this information through user-friendly dashboards, facilitating informed decisions on irrigation and fertilization (Mane et al., 2025).

Soil moisture sensors measure the volumetric water content in soil.[16]

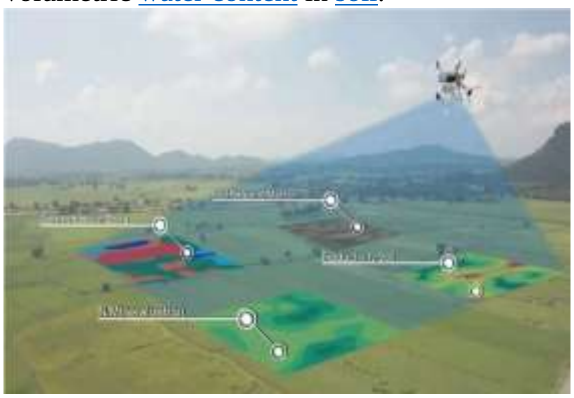

Fig 1 shows drones equipped with agriculture smart sensors which can capture high-quality images and collect data on soil nutrient levels, soil moisture, and other soil characteristics [17][18].

1.2 Objectives:

To develop AI-driven soil monitoring using Hybrid ALO-PSO optimization model.

- To analyse the performance of the hybrid model in optimizing key soil parameters such as moisture, nutrients, and pH levels.
- To implement UAV/drone-based remote sensing for real-time soil data collection and analysis.
- To compare the hybrid model's efficiency with traditional optimization techniques in terms of accuracy, convergence speed, and computational cost.

2. Literature Review

- The integration of Artificial Intelligence (AI) and optimization algorithms
- Metaheuristic Algorithms in Agriculture

o Ant Lion Optimizer (ALO) in Agriculture
o Particle Swarm Optimization (PSO) in Precision Farming
o Hybrid Approaches in Soil Monitoring

2.1 Ant Lion Optimizer in Agriculture

The Ant Lion Optimizer is a bio-inspired optimization algorithm that simulates the hunting mechanism of antlions[19]. It has been applied in soil fertility prediction, crop selection, and irrigation optimization (Sharma et al., 2022). The main advantages of ALO-include:

-Strong global search ability – Helps find optimal soil parameter configurations.

- Avoids local optima – Ensures better accuracy in soil monitoring.

However, studies have shown that ALO suffers from slow convergence rates, making it less suitable for real-time agricultural applications (Kumar et al., 2023).

2.2 Particle Swarm Optimization in Precision Farming

PSO is inspired by the social behaviour of birds and fish, making it effective in **real-time soil analysis and precision farming [19]** (Chen et al., 2023). Key applications include:

- **Optimizing soil moisture levels** to reduce water waste.
- **Improving soil classification accuracy** using sensor-based data.
- **Enhancing crop yield prediction models**.

2.3 Hybrid Approaches for Optimization

To overcome the limitations of standalone algorithms, researchers have explored **hybrid metaheuristic models** that combine multiple optimization techniques. Some key studies include:

- **Hybrid GA-PSO:** Used for soil nutrient optimization, but computationally expensive (Gao et al., 2021).
- **Hybrid ACO-PSO:** Improved precision in **irrigation scheduling and water management** (Singh et al., 2022).

2.4 UAV and Sensor-Based Soil Monitoring

- **Multispectral and hyperspectral imaging** – Analyses soil composition from drone images.
- **IoT-Based Soil Sensors** – Measures real-time parameters like pH, moisture, and nitrogen levels.

DOI: https://doi.org/10.5281/zenodo.17452079

- **AI Algorithms (CNNs, LSTMs)** – Used for soil classification and predictive analysis.

Despite these advancements, current AI models **lack real-time optimization capabilities**, making Hybrid ALO-PSO a promising approach to enhance **precision and efficiency**.

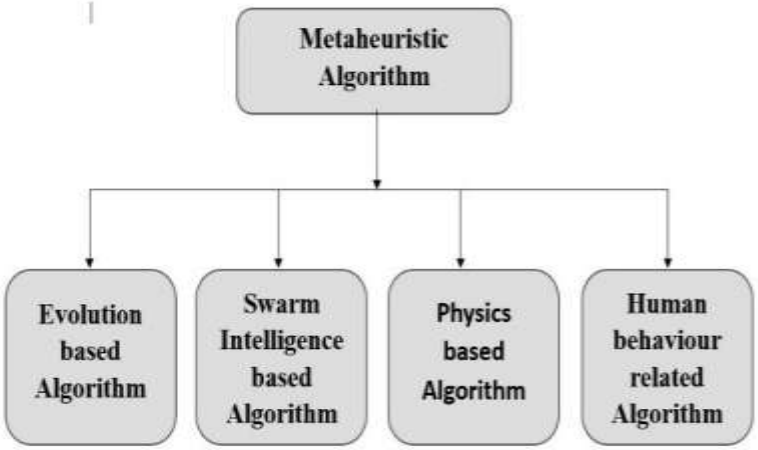

Fig 1. Classification of Metaheuristic Algorithm.

Table 1. Literature Review

Reference No.	Algorithm Name	Author Name	Year
1	Fruit Fly Optimization	W. Y. Lin	2016
2		Y. Cheng et al	2018
3	Hybrid Ant Colony	X. Wang et al	2018
4	Global Optimization	I. E. Grossmann	1996
5		R. V. Rao et al	2016
6	Grey Wolf Optimization	M. El-Kenawy	2020
7	Particle Swarm Optimization	M. Nouiri et al	2018
8	Multi-objective Optimization	Y. Li et al	2018
9	Harris Hawks Optimizer	D. Yousri et al	2020
10	Genetic Programming	R. Al-Hajj et al	2017
11	Evolutionary Computing	R. Al-Hajj et al	2016
12	Classical & non-classical	R. A. Meyers	2000
13	Quadratic Programming	N. Steffan at al	2012
14	Grasshopper Optimization	M. Mafarja et al	2018
15	Water Cycle	A. A. Heidari et al	2017

Table 2. Standard UM Benchmark Functions

DOI: https://doi.org/10.5281/zenodo.17452079

Functions	Dimensions	Range	f_{min}
$F_1(S) = \sum_{m=1}^{z} S_m^2$	(10,30,50,100)	[-100 , 100]	0
$F_2(S) = \sum_{m=1}^{z} \|S_m\| + \prod_{m=1}^{z} \|S_m\|$	(10,30,50,100)	[-10 ,10]	0
$F_3(S) = \sum_{m=1}^{z} (\sum_{n=1}^{m} S_n)^2$	(10,30,50,100)	[-100 , 100]	0
$F_4(S) = max_m\{\|S_m\|, 1 \leq m \leq z\}$	(10,30,50,100)	[-100 , 100]	0
$F_5(S) = \sum_{m=1}^{z-1} [100(S_{m+1}\text{-}S_m^2)^2 + (S_m - 1)^2]$	(10,30,50,100)	[-38 , 38]	0
$F_6(S) = \sum_{m=1}^{z} ([\ S_m + 0.5])^2$	(10,30,50,100)	[-100 , 100]	0
$F_7(S) = \sum_{m=1}^{z} mS_m^4 + random\ [0,1]$	(10,30,50,100)	[-1.28, 1.28]	0

Functions	Dimension	Range	f_{min}
$F_8(S) = \sum_{m=1}^{z} - S_m sin(\sqrt{\|S_m\|})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z} [S_m^2 - 10cos\ (2\pi\, S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp\ (-0.2\sqrt{\left(\frac{1}{z}\sum_{m=1}^{z} S_m^2\right)}) -$ $exp\ (\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(10,30,50,100)	[-32,32]	0
$F_{11}(S) = 1 + \sum_{m=1}^{z} \frac{S_m^2}{4000} - \Pi_{m=1}^{z} cos \frac{S_m}{\sqrt{m}}$	(10,30,50,100)	[-600, 600]	0
$F_{12}(S) = \frac{\pi}{z}\{10\, sin(\pi\tau_1) + \sum_{m=1}^{z-1} (\tau_m - 1)^2 [1 +$ $10 sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_{m+1}}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(10,30,50,100)	[-50,50]	0
$F_{13}(S) = 0.1\{sin^2(3\pi S_m) + \sum_{m=1}^{z} (S_m - 1)^2 [1 +$ $sin^2(3\pi S_m + 1)] + (x_z - 1)^2 [1 + sin^2 2\pi S_z)]$	(10,30,50,100)	[-50,50]	0

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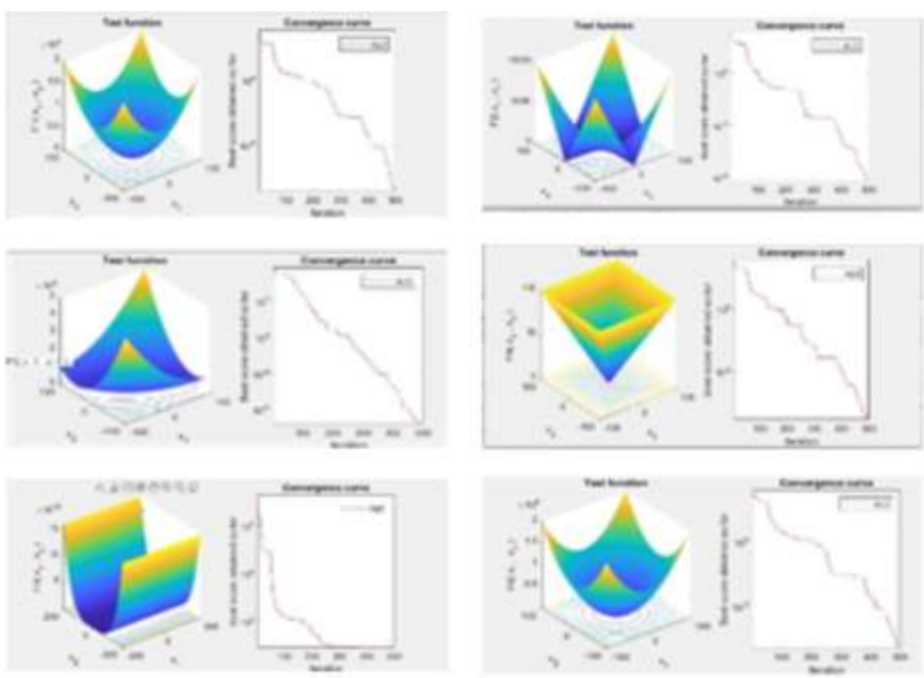
Functions	Dimensions	Range	f_{min}
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5 \frac{1}{n + \sum_{m=1}^{2}(S_m - b_{mn})^6}]^{-1}$	2	[-65.536, 65.536]	1
$F_{15}(S) = \sum_{m=1}^{11}[b_m - \frac{S_1(a_m^2 + a_m S_2)}{a_m^2 + a_m S_3 + S_4}]^2$	4	[-5, 5]	0.00030
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1 S_2 - 4S_2^2 + 4S_2^4$	2	[-5, 5]	-1.0316
$F_{17}(S) = (S_2 - \frac{5.1}{4\pi^2}S_1^2 + \frac{5}{\pi}S_1 - 6)^2 + 10(1 - \frac{1}{8\pi})\cos S_1 + 10$	2	[-5, 5]	0.398
$F_{18}(S) = \left[1 + (S_1 + S_2 + 1)^2 (19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1 S_2 + 3S_2^2)\right] \times \left[30 + (2S_1 - 3S_2)^2 (18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1 S_2 + 27S_2^2)\right]$	2	[-2,2]	3
$F_{19}(S) = -\sum_{m=1}^{4} d_m \exp(-\sum_{n=1}^{3} S_{mn}(S_m - q_{mn})^2)$	3	[1, 3]	-3.32
$F_{20}(S) = -\sum_{m=1}^{4} d_m \exp(-\sum_{n=1}^{6} S_{mn}(S_m - q_{mn})^2)$	6	[0, 1]	-3.32
$F_{21}(S) = -\sum_{m=1}^{5}[(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0,10]	-10.1532
$F_{22}(S) = -\sum_{m=1}^{7}[(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.4028
$F_{23}(S) = -\sum_{m=1}^{7}[(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.5363

3. RESULT AND DISCUSSION



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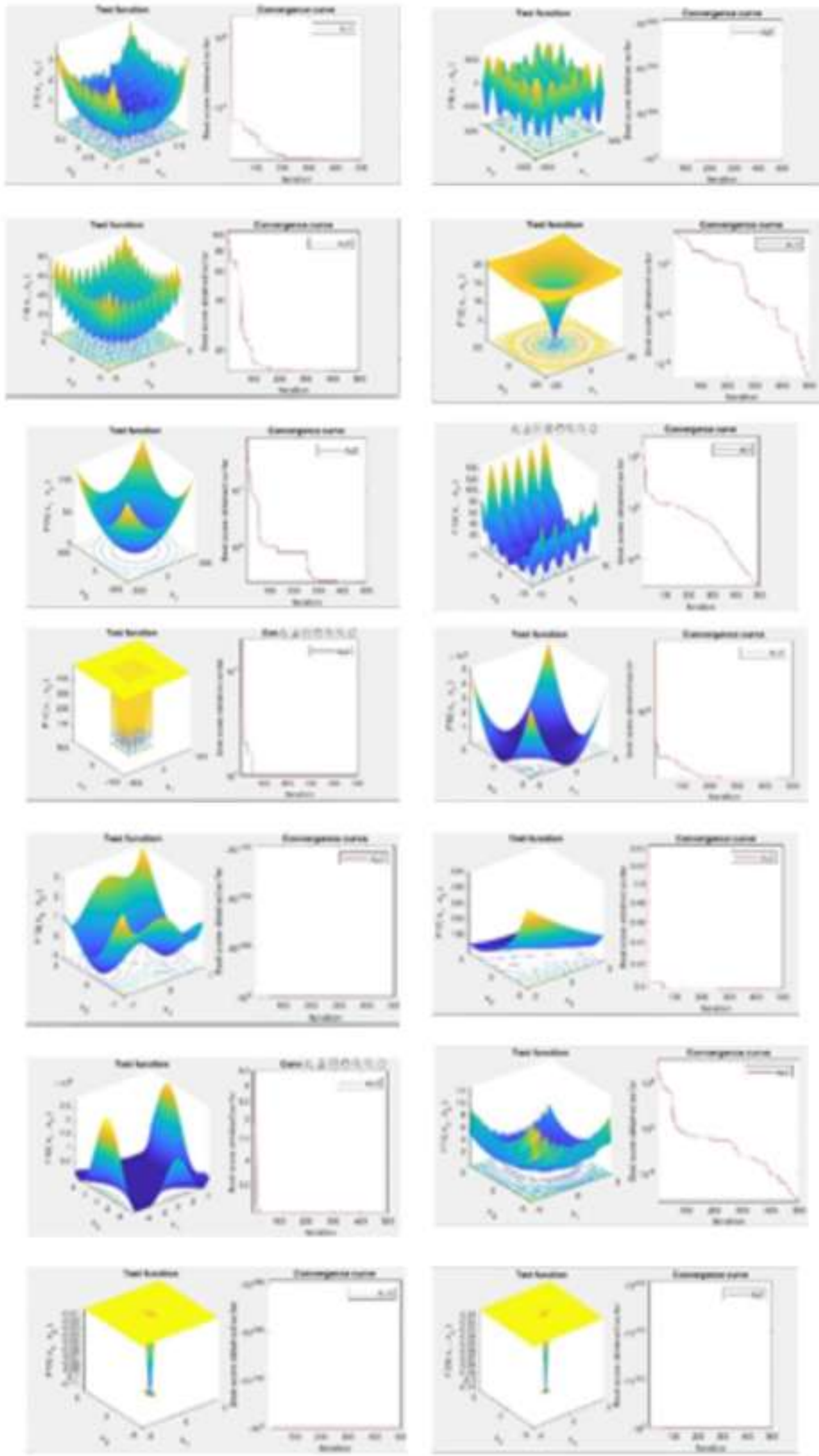

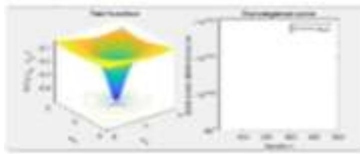

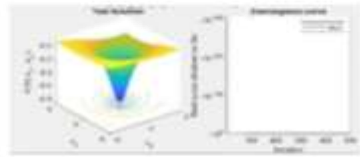

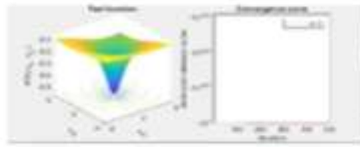

Table 3. Results for Original ALO vs Hybrid ALO with PSO

Function Number	Original Value	Hybrid Value
F1	3.31E+09	0.012591
F2	2.4173	0.24908
F3	0.00036582	0.040615
F4	0.00026785	0.061382
F5	104.1134	7.2056
F6	3.11E+09	0.011974
F7	0.0018312	0.0032233
F8	-2045.4119	-2847.3791
F9	20.8941	15.4592
F10	3.91E+05	0.44722
F11	0.39622	0.15128
F12	7.6276	0.00190207
F13	0.010987	0.0019047
F14	0.998	0.998
F15	0.00076088	0.00075839
F16	-1.0316	-1.0318
F17	0.39789	0.39788
F18	3	3.0021
F19	-3.862	-3.8621
F20	-3.2027	-3.1544
F21	-5.1008	-10.092
F22	-1.8376	-2.7505
F23	-5.1285	-10.4989

4. Conclusion

Hybridization of Ant Lion Optimizer Algorithm with Practical Swarm Optimization Algorithm was tested on 23 Benchmark functions(F1-F23) out of which it performs better and provides optimal values in 14 functions which was F2, F5, F8, F9, F11, F12, F13, F15, F16, F17, F19, F21, F22, F23. A hybrid ALO-PSO approach a better soil parameter that is exploration and exploitation. The integration of these two algorithms enhances the soil monitoring in agriculture farming. It uses UAV and sensor-based device to identify the quality of soil or we can say soil health and farming productivity. Hybrid ALO with PSO algorithm have optimises 23 key function which get indicate the strong capability of these algorithm.

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5. Future Scope

1. Testing the hybrid ALO-PSO model on agricultural lands using **IoT & sensors UAV-based on soil monitoring.**
2. By Combining AI models with optimization techniques help to improve **predictive analytics for automotive farming**.
3. **By** Evaluating the performance of the hybrid model (ALO-PSO) across **various soil types which is based upon UAV based component, it improved the integration for the algorithm.**
4. By enhancing the system for **precision farming** by integrating cloud computing and AI-based decision
5. **Energy Efficiency**: Optimizing computational resources to ensure the hybrid algorithm can run efficiently on **low-power edge devices** for real-time applications

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