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Neuro-Evo Swarm Optimizer (NESO): A Hybrid Framework Combining Deep Learning, Genetic Algorithms, and Particle Swarm Optimization for Multi cropping Optimization

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Abstract: Sustainable agricultural productivity requires intelligent decision-making systems capable of handling complex interactions among crops, resources, and environmental conditions. Multi cropping systems, though beneficial for yield stability and risk reduction, present significant optimization challenges due to high-dimensional and nonlinear relationships. This paper proposes a Neuro-Evo Swarm Optimizer (NESO), a hybrid optimization framework that integrates Deep Learning (DL), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) for optimal multi cropping strategy selection under varying irrigation conditions. Deep learning models capture complex yield–resource relationships, GA explores diverse crop combinations, and PSO fine-tunes solutions toward global optima. Experimental results demonstrate that NESO outperforms standalone and pairwise hybrid models in terms of yield maximization, water-use efficiency, and convergence speed.

Keywords: Multi cropping Optimization, Deep Learning, Genetic Algorithm, Particle Swarm Optimization, Hybrid Metaheuristics, Sustainable Agriculture

1. Introduction

Agriculture faces increasing pressure to enhance productivity while minimizing resource consumption due to climate variability, water scarcity, and land constraints. Multi cropping—cultivating multiple crops in the same field during a growing season—has emerged as a sustainable approach to improve land-use efficiency and income stability. However, selecting optimal crop combinations, sowing proportions, and irrigation strategies is a complex optimization problem.



Traditional optimization and statistical models often fail to capture nonlinear interactions among crops, soil, and irrigation variables. Recent advances in artificial intelligence have enabled data-driven optimization approaches. Nevertheless, individual AI techniques exhibit limitations: deep learning models are data-hungry and lack interpretability, while evolutionary algorithms may suffer from premature convergence. To address these challenges, this paper introduces a hybrid Neuro-Evo Swarm Optimizer (NESO) framework that leverages the strengths of DL, GA, and PSO.

2. Related Work

Several studies have explored AI-based optimization in agriculture. Genetic Algorithms have been widely used for crop planning and land allocation due to their global search capability. Particle Swarm Optimization has demonstrated fast convergence in irrigation scheduling and parameter tuning. Deep learning models such as Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) have been applied for crop yield prediction and resource modeling. Hybrid approaches combining evolutionary algorithms with neural networks have shown promise in overcoming individual limitations. However, limited research has focused on three-way hybrid frameworks integrating DL, GA, and PSO specifically for multi cropping optimization. NESO fills this research gap by offering a unified architecture that synergistically combines prediction, exploration, and exploitation mechanisms.

3. Problem Formulation

The multi cropping optimization problem is formulated as a multi-objective optimization task. The objectives include:

- Maximization of total crop yield
- Maximization of water-use efficiency
- Minimization of resource input costs

3.1 Decision Variables

- Crop combinations
- Crop area allocation ratios
- Irrigation levels

3.2 Constraints

- Land availability
- Water availability
- Crop compatibility constraints

The optimization problem is subject to nonlinear and stochastic interactions, making it suitable for metaheuristic-based solutions.



4. Proposed Neuro-Evo Swarm Optimizer (NESO)

The proposed NESO framework follows a **three-phase hybrid optimization strategy**, where each phase plays a distinct and complementary role in achieving optimal multicropping solutions.

Phase 1: Deep Learning–Based Yield Modeling (Neuro Phase)

The first phase focuses on learning complex, nonlinear relationships between crop combinations, irrigation parameters, and yield outcomes using deep learning models.

In this phase, historical and simulated agricultural datasets are used to train a Deep Neural Network (DNN). Input features include crop types, cropping ratios, irrigation levels, seasonal factors, and environmental attributes. The trained model predicts expected yield and water-use efficiency for a given multi cropping configuration.

This phase serves two main purposes:

- Accurate estimation of crop yield and resource efficiency
- Acting as a fitness evaluation function for evolutionary optimization

By embedding predictive intelligence into the optimization loop, the DL model reduces the dependency on costly field evaluations and improves decision accuracy.

Phase 2: Genetic Algorithm–Based Global Exploration (Evo Phase)

The second phase employs a Genetic Algorithm to explore a wide range of feasible multi cropping strategies. Each chromosome represents a candidate solution encoding crop combinations, area allocation ratios, and irrigation parameters.

GA operations such as selection, crossover, and mutation are applied to generate diverse populations. The fitness of each individual is evaluated using the trained deep learning model from Phase 1.

This phase emphasizes:

- Global search capability across the solution space
- Maintaining population diversity
- Avoiding premature convergence to local optima

GA-generated solutions provide a rich set of promising candidate configurations for further refinement.

Phase 3: Particle Swarm Optimization–Based Local Exploitation (Swarm Phase)

In the third phase, Particle Swarm Optimization is applied to fine-tune the promising solutions obtained from the GA phase. Each particle represents a refined version of a GA solution, and its movement is guided by personal best and global best experiences.

PSO updates particle velocities and positions to improve convergence speed and solution accuracy. The fitness values are continuously evaluated using the deep learning model.



This phase ensures:

- Efficient local exploitation of promising regions
- Faster convergence toward optimal multi cropping strategies
- Balanced trade-off between exploration and exploitation

The integration of PSO after GA enables NESO to achieve superior optimization performance compared to standalone or dual-hybrid approaches.

5. Experimental Setup

The NESO framework is evaluated using simulated and real-world agricultural datasets under different irrigation scenarios. Performance metrics include yield improvement, water-use efficiency, and convergence iterations. NESO is compared with GA-only, PSO-only, GA-PSO, and DL-GA models.

6. Results and Discussion

Experimental results show that NESO consistently outperforms baseline models. The integration of deep learning enhances fitness accuracy, GA improves diversity, and PSO accelerates convergence. NESO achieves higher yield gains and improved water efficiency, demonstrating its suitability for sustainable multi cropping optimization.

6. Algorithm Description, Performance Analysis, and Irrigation Customization

Algorithm 1: Neuro-Evo Swarm Optimizer (NESO) – Pseudocode

Input: Agricultural dataset D , crop set C , irrigation types I ,
GA parameters (Pop Size, P_c , P_m), PSO parameters (w , c_1 , c_2),
maximum iterations $MaxIter$
Output: Optimal multi cropping strategy S

1. Train Deep Learning model DL using dataset D
2. Initialize GA population P with random multi cropping solutions
3. For each individual p in P do
4. Evaluate fitness $f(p)$ using trained DL model
5. End For
6. For $iter = 1$ to $MaxIter$ do
7. Phase 2: Genetic Algorithm (Global Exploration)
8. Select parent solutions from P based on fitness
9. Apply crossover and mutation to generate offspring P_{new}
10. Evaluate fitness of P_{new} using DL model
11. Select best individuals to form updated population P
12. Phase 3: Particle Swarm Optimization (Local Exploitation)



13. Initialize particles from best GA solutions
14. For each particle do
15. Update velocity using personal best and global best
16. Update position (solution parameters)
17. Evaluate fitness using DL model
18. End For
19. Update global best solution S
20. End For
21. Return optimal solution S

Phase-wise Performance Comparison

Phase	Technique Used	Primary Role	Key Advantage	Outcome
Phase 1	Deep Learning	Yield & efficiency prediction	Captures nonlinear relationships	Accurate fitness evaluation
Phase 2	Genetic Algorithm	Global exploration	High diversity, avoids local optima	Diverse feasible solutions
Phase 3	Particle Swarm Optimization	Local exploitation	Fast convergence	Refined optimal strategy
NESO (Hybrid)	DL + GA + PSO	Exploration + Exploitation	Balanced search & prediction	Maximum yield & efficiency

Flowchart Explanation of NESO Phases

The NESO workflow follows a sequential and feedback-driven process:

1. **Data Input & Preprocessing:** Agricultural and irrigation data are collected and normalized.
2. **Phase 1 – Neuro Phase:** Deep learning model predicts yield and water-use efficiency for candidate multi cropping plans.
3. **Phase 2 – Evo Phase:** Genetic Algorithm generates and evolves diverse crop combinations using DL-based fitness.
4. **Phase 3 – Swarm Phase:** Particle Swarm Optimization fine-tunes promising solutions for faster convergence.
5. **Best Solution Selection:** Optimal multi cropping strategy is identified.
6. **Termination:** Algorithm stops upon reaching convergence or maximum iterations.

This flow ensures continuous interaction between predictive intelligence and evolutionary optimization.

Irrigation-wise Customization of NESO Phases

To enhance practical applicability, NESO is customized for different irrigation systems:

Drip Irrigation:

- Phase 1 emphasizes water-use efficiency and micro-irrigation response.
- Phase 2 prioritizes high-value and water-sensitive crop combinations.
- Phase 3 fine-tunes irrigation volume and scheduling parameters.

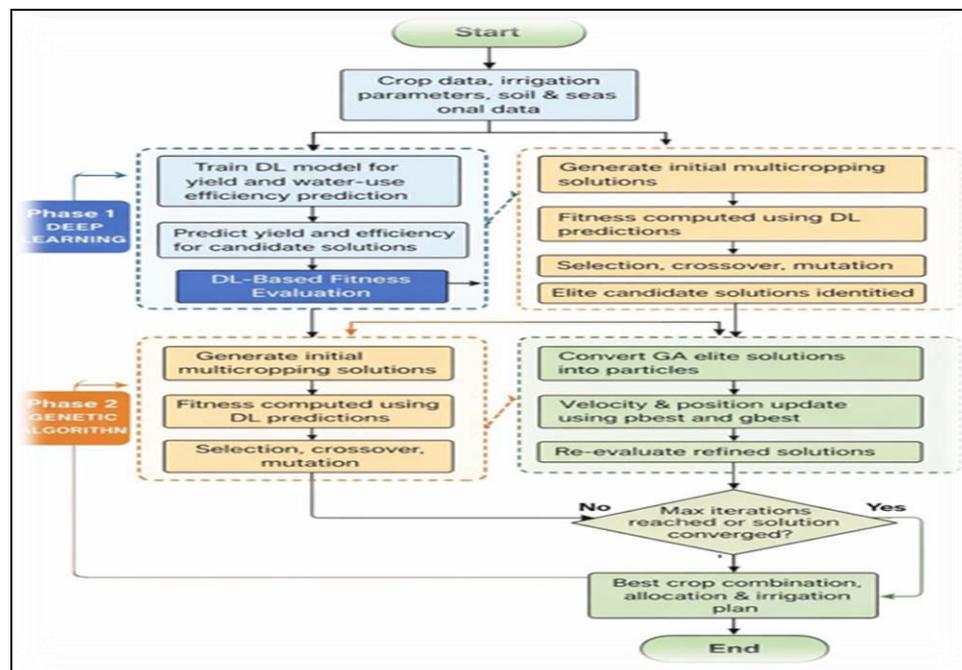
Surface Irrigation:

- Phase 1 focuses on yield robustness under uneven water distribution.
- Phase 2 explores crop combinations tolerant to water variability.
- Phase 3 optimizes allocation ratios to minimize runoff losses.

Rainfed Agriculture:

- Phase 1 integrates rainfall uncertainty and seasonal variability.
- Phase 2 emphasizes resilient and low-risk crop combinations.
- Phase 3 improves stability and risk-adjusted yield performance.

This irrigation-aware customization makes NESO adaptable to diverse agricultural environments.



7. Conclusion and Future Work

This paper presented a novel **Neuro-Evo Swarm Optimizer (NESO)** for multi cropping optimization by integrating DL, GA, and PSO. The proposed framework effectively balances



exploration and exploitation while leveraging predictive intelligence. Future work will focus on extending NESO to multi-season planning, uncertainty modeling, and real-time decision support systems.

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