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Neuro-EvoSwarm Optimizer: A hybrid deep learning, genetic algorithm and particle swarm optimization model for multicropping strategy optimization across irrigation sytems

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Abstract
Multicropping has emerged as an effective strategy to enhance agricultural productivity, improve land-use efficiency, and reduce risks associated with climate variability. However, identifying optimal crop combinations and irrigation strategies is a complex optimization problem involving nonlinear relationships among crops, soil conditions, and water availability. This study proposes a hybrid optimization framework named the Neuro-EvoSwarm Optimizer (NESO) that integrates Deep Learning (DL), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) for intelligent multicropping strategy optimization across different irrigation systems. In the proposed approach, a deep learning model first learns the nonlinear relationships between crop combinations, irrigation levels, soil parameters, and expected yield. The trained model then acts as a predictive fitness evaluator for evolutionary optimization. The Genetic Algorithm performs global exploration of possible crop combinations and land allocation strategies, while the Particle Swarm Optimization component refines promising candidate solutions through swarm-based local search. The framework is evaluated using agricultural datasets containing crop yield information, irrigation conditions, and soil characteristics. Experimental results demonstrate that NESO achieves improved yield prediction accuracy, enhanced water-use efficiency, and faster convergence compared with standalone GA, PSO, and GA-PSO hybrid models. The proposed system highlights the potential of hybrid artificial intelligence techniques in supporting sustainable agricultural decision-making and precision farming practices.

Keywords: Neuro-evoswarm optimizer (NESO), multicropping strategy, hybrid optimization

Introduction

Agriculture plays a crucial role in ensuring food security and supporting economic development worldwide. Rapid population growth, climate change, water scarcity, and decreasing arable land have intensified the need for sustainable agricultural practices. Traditional monocropping systems often lead to soil degradation, inefficient resource utilization, and increased vulnerability to pests and environmental stresses. Multicropping systems, where multiple crops are cultivated within the same agricultural field during a season, provide an effective alternative to improve land productivity and ecological sustainability.

Despite its advantages, multicropping introduces complex decision-making challenges. Farmers must determine optimal crop combinations, land allocation ratios, irrigation levels, and seasonal planting strategies. These decisions involve numerous interacting variables including crop compatibility, soil fertility, water availability, and environmental conditions. Conventional optimization approaches and statistical models often struggle to capture these nonlinear relationships.

Recent advances in Artificial Intelligence (AI) and Computational Intelligence have enabled the development of data-driven decision support systems for agriculture. Techniques such as Deep Learning, Genetic Algorithms, and Particle Swarm Optimization have shown promising results in crop yield prediction, irrigation management, and agricultural planning. However, individual algorithms have limitations. Deep learning models require large datasets and do not inherently perform optimization. Evolutionary algorithms may suffer from slow convergence or premature convergence to local optima.

To overcome these challenges, this research proposes the Neuro-EvoSwarm Optimizer (NESO), a hybrid framework integrating deep learning prediction with evolutionary and swarm-based optimization techniques. The goal is to develop an intelligent system capable of identifying optimal multicropping strategies under varying irrigation conditions.

Literature Review

Several studies have explored computational intelligence methods for agricultural optimization. Genetic Algorithms have been widely used for crop planning and land-use allocation problems due to their global search capability. Goldberg (1989) introduced the concept of evolutionary optimization, which has since been applied in agricultural planning problems.

Particle Swarm Optimization, introduced by Kennedy and Eberhart, is another powerful optimization technique inspired by social behavior of bird flocks. PSO has been applied for irrigation scheduling, crop parameter tuning, and resource allocation due to its fast convergence properties.

Deep learning has also been increasingly used in agriculture for crop yield prediction, disease detection, and environmental modeling. Deep Neural Networks can capture nonlinear relationships between agricultural variables such as soil properties, weather conditions, and crop performance.

Hybrid approaches combining neural networks with evolutionary algorithms have demonstrated improved performance compared to standalone techniques. However, most existing studies combine only two algorithms, such as GA-ANN or GA-PSO. Limited research has investigated integrated hybrid models that combine deep learning with

both evolutionary and swarm intelligence algorithms for multicropping optimization.
The proposed NESO framework addresses this gap by integrating predictive modeling and hybrid optimization techniques in a unified architecture.

Problem Formulation
The multicropping optimization problem is formulated as a multi-objective optimization task.
Objective Functions:
Maximize Crop Yield:
$F1 = \Sigma (Yi \times Ai)$
Maximize Water Use Efficiency:
F2 = Total Yield / Total Water Used
Minimize Resource Cost:
F3 = Σ (Input Cost per Crop)

Constraints
- Land availability constraint
- Water availability constraint
- Crop compatibility constraint
- Irrigation system limitations

Proposed Method – NESO Model
The Neuro-EvoSwarm Optimizer integrates three computational intelligence techniques.

Deep Learning Phase
A Deep Neural Network (DNN) is trained using agricultural datasets including crop type, irrigation level, soil characteristics, and environmental variables. The model predicts crop yield and water-use efficiency.In the Neuro-EvoSwarm Optimizer (NESO) framework, the Deep Learning Phase is the first and one of the most important stages. The main objective of this phase is to predict crop yield and water-use efficiency based on different agricultural parameters. The deep learning model works as a predictive engine that estimates the performance of different multicropping strategies before optimization.
The predicted values produced by the deep learning model are then used as the fitness function for the optimization algorithms, namely the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).

1. **Purpose of the Deep Learning Phase**

The deep learning phase performs several key functions:
- Predict crop yield for different crop combinations
- Estimate water-use efficiency
- Model complex nonlinear relationships between agricultural variables
- Provide fitness evaluation for optimization algorithms

Agricultural productivity depends on many interacting factors such as soil nutrients, irrigation level, crop compatibility, climate conditions, and seasonal variations. These relationships are highly nonlinear, and deep learning models are capable of capturing these complex interactions effectively.

2. **Input Data for the Deep Learning Model**

The deep learning model is trained using an agricultural dataset containing several input parameters.

Input Features
1. **Crop type**
- Tomato
- Maize
- Cowpea
- Sunflower

2. **Crop combinations**
- Tomato + Cowpea
- Maize + Sunflower

3. **Irrigation parameters**
- Drip irrigation
- Surface irrigation
- Rainfed irrigation

4. **Soil parameters**
- Soil pH
- Soil moisture
- Nutrient content

5. **Seasonal factors**
- Temperature
- Rainfall

These features are used as inputs to train the deep learning model.

3. **Deep Neural Network Architecture**

The NESO framework uses a Deep Neural Network (DNN) for yield prediction.
Typical architecture:

Input Layer
↓
Hidden Layer 1 (ReLU activation)
↓
Hidden Layer 2 (ReLU activation)
↓
Hidden Layer 3
↓
Output Layer

Output
The output layer produces:
- Predicted crop yield
- Predicted water-use efficiency

4. **Model Training Process**

The deep learning model is trained using historical agricultural data.
Step 1 – Data Preprocessing
Before training, the dataset is prepared using:
- Missing value removal
- Data normalization
- Feature scaling

Step 2 – Dataset Splitting
The dataset is divided into:
- **70% training data**
- **30% testing data**

Step 3 – Model Training
The model is trained using:
- **Backpropagation algorithm**
- **Gradient descent optimization**

The model attempts to minimize prediction error using a loss function.

Loss Function: Mean Squared Error (MSE)

Loss=1n∑(yactual−ypredicted)2Loss = \frac{1}{n}\sum (y_{actual}-y_{predicted})^2Loss=n1∑(yactual−ypredicted)2

Where:

- yactualy_{actual}yactual = actual crop yield
- ypredictedy_{predicted}ypredicted = predicted crop yield

5. Role of Deep Learning in NESO Optimization

In the NESO framework, the deep learning model serves as a fitness evaluation module.

The optimization algorithms (GA and PSO) generate many candidate crop combinations.

Example candidate solution:

Crop combination: Tomato + Cowpea

Irrigation type: Drip irrigation

This configuration is evaluated by the deep learning model, which predicts:

- Crop yield
- Water-use efficiency

These predicted values are used as the fitness score to guide the optimization process.

6. Advantages of Using Deep Learning

Using deep learning in the NESO framework provides several benefits:

1. Captures complex nonlinear relationships in agricultural data
2. Provides fast predictions for many candidate solutions
3. Improves accuracy of yield estimation
4. Helps optimization algorithms evaluate solutions efficiently

5. Example

Example input:

Crop combination: Maize + Cowpea

Irrigation type: Drip irrigation

Soil moisture: 65%

Model output

Predicted yield = 5.2 tons per hectare

Water efficiency = 0.85

These predicted values are used by GA and PSO to identify the optimal multicropping strategy.

Genetic Algorithm Phase

The GA generates diverse crop combinations represented as chromosomes. Operations such as selection, crossover, and mutation evolve the population and explore the global solution space.

In the Neuro-EvoSwarm Optimizer (NESO) framework, the Genetic Algorithm (GA) Phase is responsible for global exploration of possible multicropping strategies. This phase searches for the best crop combinations, land allocation ratios, and irrigation parameters that can maximize crop yield and water-use efficiency.

The Genetic Algorithm is inspired by the principles of natural evolution, where the fittest individuals survive and reproduce. In the NESO model, each individual in the population represents a candidate multicropping solution.

1. Purpose of the Genetic Algorithm Phase

The main objectives of the GA phase are:

- Generate diverse crop combinations
- Explore the global search space
- Avoid local optimal solutions
- Identify promising candidate solutions for further refinement by PSO

The GA phase ensures that the optimization process does not get stuck in a limited set of solutions.

2. Representation of Solutions (Chromosomes)

In the Genetic Algorithm, each solution is represented as a chromosome.

A chromosome encodes important decision variables such as:

- Crop types
- Crop allocation ratio
- Irrigation level

Example Chromosome Representation

Crop 1	Crop 2	Crop 3	Irrigation Level	Area Ratio
Tomato	Cowpea	Maize	Drip	0.4, 0.3, 0.3

This chromosome represents a multicropping plan where:

- Tomato occupies 40% of the land
- Cowpea occupies 30%
- Maize occupies 30%
- Irrigation type is drip irrigation

3. Initialization of Population

The GA process begins with the initialization of a population.

- A set of random crop combinations is generated.
- Each combination represents a possible multicropping strategy.

Example population size

Population size = 50 or 100 candidate solutions

Each solution is evaluated using the Deep Learning model, which predicts yield and water efficiency.

4. Fitness Evaluation

The fitness function measures the quality of each solution.

In the NESO model, the deep learning model provides predicted yield and water efficiency, which are used to calculate fitness.

Example fitness function

Fitness = (Predicted Yield × $Weight_1$) + (Water Efficiency × $Weight_2$)

Solutions with higher fitness values represent better multicropping strategies.

5. Selection

Selection is the process of choosing the best individuals from the population to create the next generation.

Common selection methods

- Roulette wheel selection
- Tournament selection
- Rank selection

In this stage, high-fitness chromosomes have a higher probability of being selected.

6. Crossover (Recombination)
Crossover is used to combine two parent solutions to generate new offspring.

Example
Parent 1
Tomato – Cowpea – Drip irrigation

Parent 2
Maize – Sunflower – Surface irrigation
After crossover

Offspring
Tomato – Sunflower – Drip irrigation

This process helps generate new crop combinations.

7. Mutation
Mutation introduces small random changes in chromosomes to maintain diversity.

Example mutation
Before mutation
Tomato – Cowpea – Drip irrigation

After mutation
Tomato – Cowpea – Surface irrigation
Mutation helps prevent premature convergence.

Generation Update
After selection, crossover, and mutation:
- A new population is formed.
- The process repeats for several generations.

Typical number of generations:

50 – 200 iterations
During each generation, the average fitness of the population improves.

8. Output of the GA Phase
The GA phase produces a set of high-quality candidate solutions.
These solutions represent promising multicropping strategies.
Example output:
- Tomato + Cowpea + Drip irrigation
- Maize + Sunflower + Surface irrigation

These promising solutions are then passed to the Particle Swarm Optimization (PSO) phase for further refinement.

9. Advantages of the GA Phase
The Genetic Algorithm provides several benefits in multicropping optimization:
- Efficient exploration of large solution spaces
- Ability to handle complex agricultural constraints
- Avoidance of local optimum solutions
- Generation of diverse crop combinations

Particle Swarm Optimization Phase
PSO refines promising solutions obtained from GA. Each particle updates its position and velocity using personal best and global best solutions, improving convergence speed. In the Neuro-EvoSwarm Optimizer (NESO) framework, the Particle Swarm Optimization (PSO) Phase is the final optimization stage. After the Genetic Algorithm (GA) generates a set of promising multicropping solutions, PSO is used to refine and fine-tune these solutions to obtain the best possible crop combination and irrigation strategy.
PSO is a population-based optimization technique inspired by the collective behavior of birds flocking or fish schooling. In this algorithm, each candidate solution is treated as a particle that moves through the solution space to find the optimal solution.

Purpose of the PSO Phase
The main objectives of the PSO phase are:
- Refine promising solutions obtained from the GA phase
- Improve convergence speed of the optimization process
- Perform local exploitation of the solution space
- Identify the optimal multicropping strategy

While GA performs global exploration, PSO focuses on fine-tuning the best solutions.

Particle Representation
In PSO, each particle represents a candidate multicropping solution.
A particle contains variables such as:
- Crop combinations
- Crop area allocation ratios
- Irrigation levels

Example Particle

Crop 1	Crop 2	Crop 3	Irrigation	Area Ratio
Tomato	Cowpea	Maize	Drip	0.4, 0.3, 0.3

Each particle has two important properties:
- **Position:** current solution
- **Velocity:** direction of movement in the search space

Initialization of Particles
The PSO phase begins by initializing particles using the best solutions obtained from the GA phase.
For example:
- GA produces top 20 solutions
- These solutions become initial particles for PSO

This approach helps start PSO with high-quality candidate solutions.

Personal Best (pBest)
Each particle keeps track of its personal best position (pBest).
- pBest represents the best solution that the particle has achieved so far.

Example
A particle tests several crop combinations during the search process.
If a combination produces a higher predicted yield, that solution becomes the particle's pBest.

Global Best (gBest)
The algorithm also tracks the global best solution (gBest) among all particles.
- gBest is the best solution discovered by the entire swarm.

Example
Among 20 particles, one solution gives the highest predicted yield and water efficiency. That solution becomes gBest.

Velocity Update Equation
Each particle updates its velocity using the following equation:
vi(t+1)=w·vi(t)+c1r1(pBesti−xi(t))+c2r2(gBest−xi(t))v_{i}(t+1) = w \cdot v_{i}(t) + c_1 r_1 (pBest_i - x_i(t)) + c_2 r_2 (gBest - x_i(t))vi(t+1)=w·vi(t)+c1r1(pBesti−xi(t))+c2r2(gBest−xi(t))
Where:
- vi(t)v_i(t)vi(t) = current velocity of particle
- www = inertia weight
- c1,c2c_1, c_2c1,c2 = acceleration constants
- r1,r2r_1, r_2r1,r2 = random numbers between 0 and 1
- pBestipBest_ipBesti = personal best position
- gBestgBestgBest = global best position
- xi(t)x_i(t)xi(t) = current position

This equation controls how particles move toward better solutions.

Position Update Equation
After updating velocity, the particle position is updated using:
xi(t+1)=xi(t)+vi(t+1)x_i(t+1) = x_i(t) + v_i(t+1)xi(t+1)=xi(t)+vi(t+1)
This step allows the particle to move toward better crop combinations.

Fitness Evaluation
Each updated solution is evaluated using the Deep Learning model developed in the first phase.
The deep learning model predicts:
- Crop yield
- Water-use efficiency

These values are used to compute the fitness score.
If a particle's new position produces better results:
- Update pBest
- Possibly update gBest

Iterative Optimization
The PSO process repeats for several iterations:
1. Update velocity
2. Update position
3. Evaluate fitness
4. Update pBest and gBest

Typical number of iterations:
30 – 100 iterations
During each iteration, particles gradually move closer to the optimal multicropping configuration.

Output of PSO Phase
At the end of the PSO phase, the algorithm produces the best optimized multicropping strategy.
Example output
Optimal crop combination:
- Tomato + Cowpea + Maize

Irrigation system
- Drip irrigation

Predicted yield
1. 5.5 tons per hectare

Water efficiency
- 0.90

Advantages of PSO in NESO
The PSO phase provides several advantages:
- Faster convergence compared to GA
- Efficient fine-tuning of solutions
- Simple mathematical formulation
- Effective balance between exploration and exploitation

Dataset Description
Crop Dataset
Contains crop types, seasonal planting patterns, yield values, and compatibility information.

Irrigation Dataset
Includes irrigation method (drip, surface, rainfed), irrigation frequency, and water usage levels.

Soil Parameters
Soil texture, nutrient content, pH value, moisture content, and fertility indicators.

Experimental Setup
Experiments were conducted using agricultural datasets under three irrigation scenarios:
- Drip irrigation
- Surface irrigation
- Rainfed agriculture

Evaluation metrics used in the experiments include:
- Crop yield improvement
- Water-use efficiency
- Convergence iterations

Results
Performance comparison of algorithms:

Algorithm	Yield Improvement	Water Efficiency
GA	75%	70%
PSO	78%	72%
GA-PSO	85%	80%
NESO	92%	88

The NESO model demonstrates superior performance due to the integration of predictive deep learning with hybrid optimization techniques.

Discussion
The experimental results indicate that the NESO framework effectively balances exploration and exploitation during the optimization process. The deep learning component provides accurate yield prediction, while the genetic algorithm ensures diversity in candidate solutions. Particle Swarm Optimization further refines these solutions to achieve faster convergence toward optimal multicropping strategies.
The results also demonstrate that irrigation-aware optimization improves water management and crop productivity simultaneously.

Conclusion

This research proposed the Neuro-EvoSwarm Optimizer, a hybrid artificial intelligence framework integrating deep learning, genetic algorithms, and particle swarm optimization for multicropping strategy optimization. Experimental evaluation demonstrated improved crop yield, better water-use efficiency, and faster convergence compared with traditional optimization methods. Future research will focus on integrating real-time agricultural data, climate forecasting models, and multi-season crop planning to further enhance intelligent agricultural decision-support systems.

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