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# Multi-objective particle swarm optimization for regional crop planning

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Land, water and soil nutrients are important natural resources in agriculture (Jain *et al.* 2017). In agriculture, the main challenge is resource management, such as climate change, land allocation, irrigation water management and other which can be controlled by effective crop planning (Jain *et al.* 2018a, 2018b). These crop planning models are based on the concept of linear programming and take a single objective function (Jain *et al.* 2019). With the advent of open data policy, optimization software, and new programming paradigms like R and Python, it is now possible to develop multi-objective optimal crop plans regionally (Nath *et al.* 2020).

In Multi-objective Optimization (MOO) problems, the objective functions are said to be conflicting, and there exist several pareto-optimal solutions. Several researchers have developed approaches for solving MOO problems (Begam *et al.* 2021). The traditional approaches struggle with multi-objective search and optimization depending upon the domain. However, evolutionary algorithms are expected to outperform traditional approaches and other blind search tactics (Nath *et al.* 2020). There is a lack of collective expertise in agriculture crop planning and evolutionary computing among researchers. Therefore, very few attempts are available in the literature using evolutionary concepts of optimization. In the present study, a multi-objective Particle Swarm Optimization (PSO) based crop planning technique was used for Bundelkhand, which is one of the water deficit regions of the country with uncertain precipitation using the data of the year 2017–18, (Jain *et al.* 2020). The results were compared with single-objective PSO, and linear programming approach.

*Particle Swarm Optimization (PSO)*

PSO is an evolutionary technique (based on the social behaviour of a bird flocking and fish schooling), developed for optimization of continuous non-linear, constrained and unconstrained, non-differentiable multimodal functions (Kennedy 2010).

In order to understand PSO, consider a swarm containing p particles in a K–dimensional continuous solution space. The best particle is denoted as gbest in the swarm. The best previous position of the $i^{th}$ particle is recorded and represented as pbest ($p_i$). The velocity of each particle is represented by equation 1 and 2.

$$v^t_i = W \times v_i^{t-1} + c_1 r_1 \, (pbest_i^{t-1} - x_i^{t-1}) + c_2 r_2 \, (gbest_i^{t-1} - x_i^{t-1}) \quad (1)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (2)$$

In these equations, W, inertia weight; c1 and c2, acceleration coefficients; r1 and r2, random numbers between 0 and 1; v, particle velocity; x, particle position; i, $i^{th}$ particle in a swarm and; t, $t^{th}$ iteration number in the optimization process.

*Multi-objective Particle Swarm Optimization with Crowding Distance (MOPSOCD)*

A MOO problem provides a set of solutions in which the non-dominated solution set is called the Pareto-optimal set. A multi-objective PSO is a well-organized algorithm but it has one major frailty of falling into a local optimal solution. MOPSOCD makes use of Crowding Distance (CD) to overcome the problem of local optimum solutions (Raquel *et al.* 2005). CD is the average distance of its two closest neighboring solutions. The high crowding distance value indicates a lower density of the individual distribution and a higher diversity of the solution and vice versa (Fig 1).

*MOO for crop planning model*

Dataset: Bundelkhand region of India is selected based on their agricultural versatility and need for crop planning. Dataset has been prepared following the methodologies in literature (Jain *et al.* 2019). Data has been collected from "Comprehensive Scheme for Studying the Cost of Cultivation of Principal Crops, 2017–18'', Directorate of Economics and Statistics, Ministry of Agriculture,

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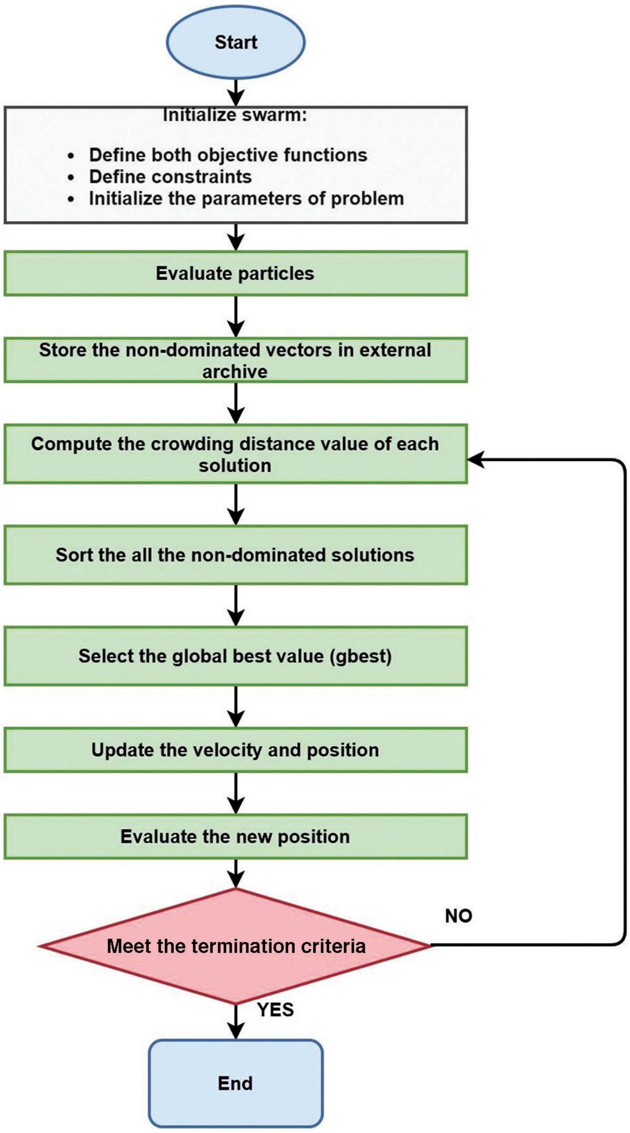


Fig 1 Flow chart of MOPSOCD work.

Government of India (DES 2018). The other secondary data sources were used, viz. Central Ground Water Board, Ministry of Water Resources as per literature (Chand *et al.* 2020). Crop based input-output and return coefficients include water, cost of cultivation, yield and net returns per hectare of land under the crop. The crop calendar is an identity matrix to denote the growing months for each crop.

*Model formulation (Objective functions)*

Maximizing total net returns: The objective is to maximize the net return (NR) based on the optimum crop plan.

$$\text{Max NR}=\sum_{c=1}^{n}(Y_cP_c-C_c)A_c \tag{3}$$

Here $Y_c$, denotes the yield of a crop c in one hectare of land; $P_c$, revenue from the output of a crop c; Cc, cost obtained to cultivate crop c in one hectare of the area and; Ac, area under cultivation of crop c.

Minimizing water requirement: The study's second objective function is to reduce the overall amount of water required, referred as WR, for crop cultivation (equation 4).

$$\text{Min WR}=\sum_{c=1}^{n}(W_c)A_c \tag{4}$$

$W_c$, denotes water required for crop c in one hectare of land. In case of single objective models, this objective is formulated as a water constraint.

$$\sum_{c=1}^{n}(Wc)A_c \leq W_a \tag{5}$$

$W_a$, the total available water for irrigation.

*Model formulation (Restrictive conditions)*

Constraints are a set of conditions that are required to be satisfied to achieve the optimal results.

Area constraint: Total area under cultivation in the region should be less than or equal to the sum of the amount of land allocated by the model for each crop (equation 6).

$$\sum_{c=1}^{n}(a_{tc})A_c \leq NC_t \tag{6}$$

$a_{tc}$, refers to the coefficient of crop calendar matrix for $t_{th}$ month and $c_{th}$ crop.

Minimum and maximum constraints: Area for a particular crop should be in between the maximum and minimum area as mentioned in equation 7 and 8 that is specified by the experts according to the needs of the region.

$$A_c > A_{minC} \tag{7}$$

$$A_c > A_{maxC} \tag{8}$$

*Model formulation (Experimental setting):* All the evolutionary algorithms are associated with certain parameters that should be fine-tuned so that the algorithms give the best result. The parameter selection in the presented work was done by experimenting with the parameter in an ordered range and selecting the ones that gave the best results are presented in Table 1. This study is implemented using R and GAMS software with number of packages like MOPSOCD, PSO, GGPLOT2, MCO and related packages.

The present study gives number of pareto-optimal solutions. These solutions reveal the probable area for

Table 1 Experimental setting for MOPSOCD and single-objective PSO algorithms model

| Parameter | MOPSOCD settings | Single-objective PSO settings |
|---|---|---|
| Population size | 500 | 500 |
| Inertia weight (w) | 0.7 | 0.83 |
| Acceleration constants (a1 and a2) | 2.0 and 0.90 | 2.0 and 0.90 |
| Objective function | 2 | 1 |
| Constraints | 2 | 3 |
| Variable number | 26 | 26 |

Table 2 Per cent of change in area allocation to different crops using MOPSOCD, PSO and LP

| Crop | Per cent of changes w.r.t. existing used area (%) | | |
|---|---|---|---|
| | MOPSOCD | PSO | LP |
| Arhar | 46.70 | 31.67 | 49.96 |
| Bajra | 8.98 | 32.48 | 45.31 |
| Barley | 15.28 | 4.85 | 0.00 |
| Berseem | 66.24 | 629.85 | 0.00 |
| Chillies | -51.47 | -5.34 | 36.91 |
| Chickpea | 42.70 | 10.44 | 49.99 |
| Groundnut | 32.28 | 33.67 | 49.83 |
| Guar | 681.52 | 764.45 | 949.56 |
| Jowar | 32.17 | 47.72 | 48.55 |
| Khesari | 761.02 | 584.75 | 0.00 |
| Lentil | 36.99 | 30.42 | 0.96 |
| Linseed | 22.38 | 23.02 | 0.00 |
| Maize | 10.11 | 16.75 | 43.94 |
| Mentha | -61.26 | -45.59 | -21.05 |
| Mesta | 810.32 | 29.79 | 74.00 |
| Moong | 43.96 | 46.03 | 48.52 |
| Mustard | -59.92 | -67.98 | -13.48 |
| Onion | 0.31 | -78.12 | 29.16 |
| Paddy | 33.29 | 29.68 | 50.01 |
| Pea | 2.48 | 13.41 | 0.00 |
| Sesamum | 38.33 | 46.80 | 46.80 |
| Soybean | 55.58 | 55.70 | 56.27 |
| Sugarcane | -6.26 | -18.89 | 0.00 |
| Tomato | 475.27 | 361.84 | -100.00 |
| Urad | 48.24 | 48.67 | 49.22 |
| Wheat | 46.70 | 31.51 | -89.54 |
| Net returns (Billion ₹) | 122–134 | 140 | 132 |

individual grown crops concerning their maximum net return and minimum water requirement. Obtained results of a designed multi-objective model are compared with results of single objective function models, PSO and linear programming approach. Table 2 shows the crop areas decided by crop planning optimization using MOPSOCD, PSO and LP compared with existing areas based on previous cropping patterns.

We observe that the area under some water consuming crops (chilly, mentha, sugarcane etc.) decreases while area allocation increases under rainfed and less water consuming crops. These possible solutions provide the information about the allotted area for different crops with the expected net return and water requirement. MOPSOCD model provides the net return values from different solutions ranging from ₹122–134 billion whereas single-objective PSO provides ₹140 billion and using LP got ₹132 billion with the same data sets.

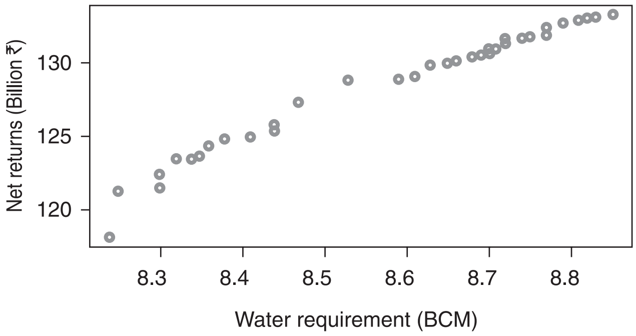


Fig 2 Relationship between net returns and water requirements using pareto-optimal solutions.

MOPSOCD based pareto-optimal solutions are plotted in Fig 2. It shows the linear pattern between net return and water used for crop planning and shows that increase in water availability helps to get higher net returns.

The multi-objective PSO algorithm finds the non-dominated solutions presented by pareto-front. It implements the crowding distance mechanism for improving the functionality of PSO. MOPSOCD searches the multiple solutions, denoted by pareto-optimal front, as compared to single objective PSO and LP. Pareto-optimal solutions reveal the relationship between net returns and water requirement. This relationship helps the stakeholders to identify the suitable plan based on the water availability in Bundelkhand region.

## SUMMARY

Indian agriculture is heavily dependent on natural resources and climatic situations etc. Uncertain behaviour of climate and continued depletion of natural resources can cause food security issues due to low production. Optimal crop planning is one of the essential tasks for utilizing the minimum resources to acquire the maximum benefit. A novel crop planning model is proposed here for the optimal allocation of available resources under a water scarred region like Bundelkhand using data for the year 2017–18. This study used an evolutionary algorithm called Multi Objective Particle Swarm Optimization using Crowding Distance, to solve the constrained multi-objective crop planning problems. Maximize net returns and minimize the water requirement were the two objective functions used here with area constraints. The optimized results obtained from the multi-objective model were compared with the single objective PSO and linear programming approach. Overall, optimizing the water requirement instead of taking it as a constraint gives better crop planning strategies by allocating the area to suitable crops. Pareto-optimal solutions obtained from the MOPSOCD shows the linear relationship between net returns and water.

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