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Democratization of Crop Irrigation: A Socio-Technical Optimization Approach Using Particle Swarm Optimization

Hasna Elalaoui Elabdallaoui[1,a,*], Youssef Mourdi[2,b], Abdelaziz ElFazziki[1,c], Mohamed Sadgal[1,d]

[1]*Computer Systems Engineering Laboratory, Faculty of Sciences, Cadi Ayyad University, Marrakech, Morocco*
[2]*Modeling and Combinatorics Laboratory, Poly-disciplinary Faculty, Cadi Ayyad University, Safi, Morocco*
[*]*Corresponding author*

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A B S T R A C T

This article explores an intelligent and equitable approach to collective and participatory irrigation for small farmers, with an emphasis on the democratization of water use. It examines how this equitable irrigation approach can contribute to the social economy by improving irrigation efficiency and reducing costs for farmers. This work highlights the socio-economic benefits of this approach and highlights its potential to promote democratic water management particularly for small-scale farmers. To do this, we propose a collective irrigation system using a Particle Swarm Optimization (PSO) algorithm, to accurately estimate crop water needs, a method of equitable distribution of water according to needs. Additionally, we propose a novel weighted aggregation technique to establish irrigation priorities among crops, taking into account factors such as crop yield, water scarcity, and economic value.

[a] *h.elalaoui@uca.ac.ma* *https://orcid.org/0000-0002-4668-9806*
[b] *y.mourdi@uca.ac.ma* *https://orcid.org/0000-0003-0999-6388*
[c] *elfazziki@uca.ma* *https://orcid.org/0000-0002-0302-234X*
[d] *sadgal@uca.ma* *https://orcid.org/0000-0002-1087-0988*

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Introduction

Irrigation plays a crucial role in agriculture, especially for small farmers who often rely on limited water resources. However, several problems and challenges effectively hinder this irrigation, which requires special attention and suitable solutions. This section examines these challenges and highlights the importance of finding innovative approaches to overcome them (Koech & Langat, 2018; Levidow et al., 2014; Saad et al., 2020; Zinkernagel et al., 2020).

- Limited access to water: Small farmers often face difficulties accessing water for irrigating their land. In many regions, water resources are scarce and are often monopolized by large agricultural operations or other sectors. This significantly limits the availability of water for family farmers, thereby compromising their livelihoods.
- Inefficient water management: Even when water is available, its inefficient management can lead to wastage and sub-optimal use of resources. Traditional irrigation methods can be inefficient and imprecise, leading to overuse or underuse of water, which negatively affects crop yields and farmers' savings.
- High costs: Costs associated with irrigation, such as water pumping fees and irrigation equipment, can be prohibitive for small farmers with limited resources. These high costs can make the adoption of modern, efficient irrigation technologies out of reach for many smallholder farmers.
- Lack of knowledge and technology: Small-scale farmers may also face a lack of knowledge and access to modern irrigation technologies. They may not be aware of best irrigation practices or available technologies to improve water use efficiency. This limits their ability to optimize their use of available water resources.

Faced with these challenges, it becomes imperative to develop innovative and accessible solutions to promote efficient and sustainable irrigation among small farmers. The application of machine learning algorithms in the context of collective irrigation (Gonzalez Perea et al., 2021; Ikidid et al., 2021; Torres-Sanchez et al., 2020; Wei et al., 2022) offers a promising opportunity to address these challenges by improving water management, reducing costs and democratizing access to water technologies.

In addition, collective irrigation, when integrated into the framework of the social and solidarity economy, pursues several essential objectives aimed at promoting the well-being of small farmers and strengthening the sustainability of agricultural systems (Basso & Antle, 2020; Khatoon et al., 2020; Klerkx & Begemann, 2020).

This paper examines these objectives and highlights their importance in promoting democratic water management and an inclusive social economy: Strengthen solidarity and cooperation, promote social inclusion, improve environmental sustainability and increase resilience to climate change.

To do this, we offer an intelligent irrigation system with collective and participatory management that benefits both farmers and their communities, while promoting democratic and equitable water management.

The reminder of this paper is structured into many sections: In the first sections, we present the key notions raised in this contribution, namely the democratization of irrigation, the collective social economy (crowdfunding) while exposing some works in the literature that have addressed the same subject. The following section is reserved for the presentation of the general overview of the problem addressed, the proposed approach and the PSO algorithm as the technical solution adopted. The implementation details and the results obtained are discussed towards the end of the article.

Crop irrigation, democratization and collective management

A collective and participatory irrigation project for small farmers aims to bring together several farmers to manage the irrigation of their crops together. This type of project allows farmers to share the costs of installing and maintaining irrigation infrastructure, and reducing the financial burden on each individual. Additionally, by using technologies like blockchain, farmers can monitor and manage irrigation more efficiently, saving water and increasing yields.

Crop irrigation is a crucial part of ensuring optimal agricultural yields, especially for small-scale farmers who often rely on natural rainfall. The democratization of irrigation (Ibrahim Mohammad Abuzanouneh et al., 2022; Sanchis-Ibor et al., 2020), by making this resource more accessible and efficient for small farmers, can have a profound impact on their socio-economic lives. Socio-economic benefits include:

- Water conservation: More efficient use of water through smart irrigation systems can help conserve water resources, which is crucial in areas where water is scarce.
- Increased yields: By providing the right amount of water at the right time, smart irrigation can increase agricultural yields, which translates into increased income for farmers.
- Cost reduction: By optimizing water and energy use, farmers can reduce their production costs, which can increase their profitability.
- Collective management: Collective irrigation management involves farmers in a given region working together to manage and maintain their irrigation systems collectively.
- Community strengthening: Collective management promotes cooperation and solidarity among farmers, thus strengthening the social fabric of the agricultural community.
- Resource sharing: Farmers can share water and irrigation infrastructure equitably, ensuring that all community members benefit from access to water.
- Conflict Reduction: By collectively managing irrigation, farmers can reduce water-related conflicts, which can benefit the social and economic stability of the region.

Crowdfunding is participatory financing (Saiti et al., 2018; Tambi, 2022). It is a form of fundraising through platforms that connect investors on one side and project leaders on the other. Furthermore, crowdfunding constitutes a great opportunity for start-ups because it does not restrict the number of projects that investors can finance.

Also Crowdfunding can be an effective way to raise funds for smallholder irrigation projects. By using principles of Islamic finance, farmers can benefit from the following benefits:

- Access to finance: Small farmers who struggle to obtain loans from traditional financial institutions may find easier access to crowdfunding based on Islamic finance.
- Community participation: By involving the community in financing irrigation projects, farmers can strengthen community ties and benefit from community support for their projects.
- Risk sharing: Crowdfunding allows risks to be shared between investors and farmers, which can reduce financial pressure on the latter.

Democratizing irrigation for smallholder farmers, by promoting practices such machine learning, collective management and crowdfunding under Islamic finance, can have a significant impact on their lives socioeconomic. These practices can contribute to more efficient use of resources, increased agricultural yields and stronger farming communities, which can lead to an overall improvement in the well-being of smallholder farmers.

A brief literature review: Smart irrigation and democratization of water irrigation

Where water is scarce, water management becomes vital. The management of irrigation systems remains a central point in the field of agriculture, an economically crucial area for certain countries around the world. With the water shortage experienced by the entire planet Earth, several implementations have resorted to the integration of innovative techniques and technologies. This section presents recent improvements made in the literature to the problem of efficient water management.

Most of this work focuses on ‘Smart Irrigation’, which is more efficient and more relevant in helping with decision-making. From machine learning to the Internet of Things, smart irrigation improves performance and is an emerging technique to automate irrigation systems and save water usage.

According to (Obaideen et al., 2022), an intelligent irrigation system is a multidimensional system that takes into consideration several aspects including data acquisition, fault detection, data processing, (wireless) communication and irrigation control.

Concerning the democratization of water irrigation, this study (Matos & Dias, 2023) explores the concept of water democracy and proposes solutions for more inclusive and participatory water governance, highlighting the emphasis on the rights of local communities to access and manage water resources.

Another study (Masood Ahmed & Eduardo Araral, 2019) analyzes the governance mechanisms of irrigation water in India and offers recommendations for more democratic management and participatory water.

This FAO report (David Molden, 2013) examines the challenges of water management in agriculture and highlights the importance of participation farmers and local communities in the sustainable management of water resources.

This work (Barbara Rose Johnston, 2012) explores the links between water, cultural diversity and environmental change, highlighting the importance of recognizing and respecting the management knowledge and practices of local communities some water.

These various studies and publications highlight the importance of promoting more democratic and participatory water management, by recognizing the rights and knowledge of local communities in the management of irrigation water resources.

Crowdfunding: a collaborative financing

The term “Crowdfunding” was used for the first time by Michel Sullivan in 2006. Originally the model was used for charitable works (Beaulieu et al., 2015) but currently it is used to finance several types of projects.

Collaborative financing is a very important source of financing. In Europe, thousands of projects are financed by this mechanism, which otherwise would not have received funding. Furthermore, in recent decades, all over the world we have witnessed the establishment of start-ups based on Islamic financial contracts applying financial technology. They are called “Islamic crowdfunding platforms”. These platforms are characterized by heterogeneity in the type of financing.

A good and innovative idea is to combine crowdfunding with the blockchain technology. The initial coin offering (ICO), where start-ups use blockchain protocols and the mechanisms of cryptocurrency tokens as a means of crowdfunding their businesses, has become an innovation. For example, crowdfunding platforms such as Swarm and Lighthouse allow a company to create its own cryptocurrency that can be exchanged for other currencies (Peter Baeck & Liam Collins, 2015).

Table 1 summarizes the differences between traditional financing and financing passed via a blockchain.

The advantages of financing via blockchain technology are numerous. Among which the possibility of:

- Introducing a voting system based on blockchain to allow the public be involved in corporate governance in a cost-effective manner (Zhu & Zhou, 2016)
- Use smart contracts to track all changes between the crowd and project sponsors, to detect fraudulent fundraising practices (Asma’ Tajul Arifin et al., 2018);
- develop an identity management system that gives full control to users via blockchain (Asma’ Tajul Arifin et al., 2018), preventing identity theft and money laundering;
- implement a digital currency like bitcoin to avoid intermediaries like banks and payment providers (Peter Baeck & Liam Collins, 2015)
- establish the conditions under which a transaction takes place, helping regulators observe and regulate the investment quota and qualification of investors (Asma’ Tajul Arifin et al., 2018)

This contribution ‘promoting crowdfunding within the blockchain technology’ will not be discussed here, but will be published in a forthcoming paper, given that we are treating the case of small farmers.

Particle Swarm Optimization (PSO)

Kennedy and Eberhart proposed in 1995 Particle Swarm Optimization (PSO), a stochastic meta-heuristic nonlinear optimization algorithm, intended to solve complex computational problems related to optimization.

General overview

Particle Swarm Optimization (PSO) draws inspiration from nature, observing how schools of birds and fish adapt their physical movements to avoid predators, search for food, find mates or optimize environmental parameters such as temperature.

Table 1. Traditional financing vs. Financing via blockchain

	Traditional Financing	Financing via Blockchain
Bottleneck efficiency	Compensation process complex; Involving manual inspection; Many intermediate entities	Distributed ledger; Automated disintermediation
Security of funds management	A central trust party; Complex share transaction and transfer	point-to-point transmission; Uniqueness of the transaction and transfer of equity
Cost	Very high	Very low
Transaction delays	Centralized data management; Leads and lags	Decentralized management of data; Transactions are time-stamped and can be verified in near real time
Operating risk	Use of asymmetric information which often leads to adverse selection and moral hazards; Double payment	Use of asymmetric encryption; Transparent

Table 2. PSO parameters and their possible values

PSO Parameter	Role	Possible values	Conclusion
Swarm size	Determine the number of particles in the set	empirical studies show that PASO has the ability to find optimal solutions with small swarm sizes of 10 to 30 particles	A large swarm allows larger parts of the search space to be covered per iteration.
Number of iterations	The only stopping condition on which PSO is based	Too few iterations can end the search prematurely. Too many iterations results in unnecessary additions in terms of computational complexity	Depends on the problem. It is better to carry out several tests and compare the solutions obtained
Inertia coefficient w	determines how well the particle should maintain its previous speed	• w ≥ 1, speeds increase with time, accelerating towards maximum speed • w < 1, the particles decelerate until their speeds reach zero • Large values for w make exploration easier, with increased diversity. A small w favors local exploitation	used a static value for the entire search duration, for all particles in each dimension.
Cognitive coefficient c1	determines how confident the particle is	• c1 = c2 = 0, particles continue flying at their current speed until they reach a limit of the search space • If c1 > 0 and c2 = 0, each particle finds the best position in its neighborhood by replacing the current best position if the new position is better. The particles perform a local search.	• Usually taking static values. • Most applications use c1 = c2, the ratio between these constants depends on the problem. • Low values for c1 and c2 allow particles to move away from good regions to explore before being brought back to good regions. • Higher values cause more acceleration, with abrupt movement toward or beyond the right regions.
Social coefficient c2	measures the trust of a particle in its neighbors	• if c2 > 0 and c1 = 0, the whole swarm is attracted towards a single point, • If c1 >> c2, each particle is much more attracted to its own best position, resulting in excessive wandering. • if c2 >> c1, particles are more strongly attracted to the best overall position, causing particles to rush prematurely toward the optima.	

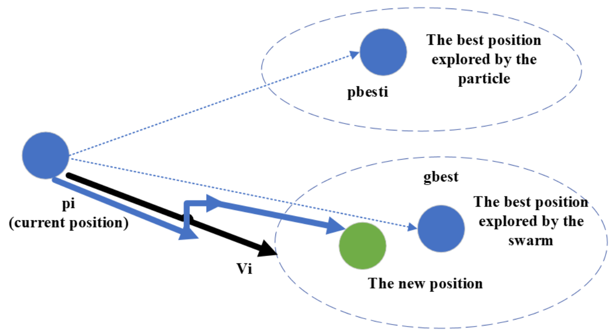


Figure 1. pbest and gbest solutions

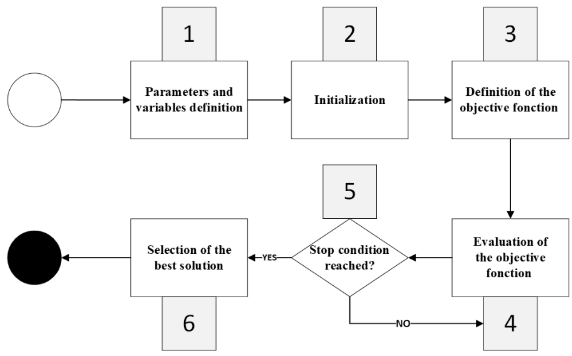


Figure 2. The PSO process

A flock of birds that evolves in a group "can benefit from the experience of all the other members". For example, if one bird in this group is looking for food, all the others help and share according to their expertise.

Birds and fish leverage the swarm's collective intelligence, social behavior, and movement dynamics to exchange information within their group, increasing their survival advantage.

The algorithm principle

The goal of PSO optimization is to find the optimal function that either maximizes the accuracy or precision or minimizes the loss.

The objective of PSO is to find a global optimum on a search space. A swarm in the algorithm is represented by a set of particles [x1, x2, x3, …, xn] and the objective is to minimize or maximize a proposed optimization function f(x).

The algorithm follows these steps:

- We start with a random set of points (particles)
- Each particle searches for the best position (solution) in random directions
- Each particle searches around the optimal point that it has found and that found by the other particles (At each iteration, an update of the positions is carried out)

After a certain number of iterations, the best solution is the one explored by the entire swarm

Formalization

Suppose we have P particles and we denote the position of particle i at iteration t as $X_i(t)$. Besides the position, we also have a velocity for each particle, denoted $V_i(t)$. In the next iteration, the position of each particle would be updated as:

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

and at the same time, the speeds are also updated by the rule:

$$V_i(t+1) = w\, V_i(t) + c_1 r_1 \left(pbest_i - X_i(t)\right) + c_2 r_2 \left(gbest - X_i(t)\right)$$

Where r1 and r2 are random numbers between 0 and 1, constants w, c1, c2 are parameters of the PSO algorithm. C1 and C2 are particle refinement weights that control the trade-off between exploitation and exploration. pbesti is the position which gives the best value ever explored by a particle i and gbest is the best explored by all the particles of the swarm (see Figure 1).

PSO parameters

The basic PSO is determined by various control parameters, such as problem dimension, number of particles, acceleration coefficients, inertia weight, neighborhood size, number of iterations, and random values which modulate the contribution of cognitive and social components.

Several authors in the literature (Jain et al., 2022; Thomas Bartz-Beielstein et al., 2002) have tried to study these parameters and see how their values/modifications can have an influence on the convergence of the solution. The Table 2 below summarizes the contributions of our literature review on this subject:

Materials and Methods

The problem that we deal with in the present consists of modeling the distribution of water in an irrigation system by referring to the PSO method. The objective is to maximize irrigation efficiency while minimizing water consumption.

Problem Modeling

We formulate the problem as follows: we consider that we have a certain number of cultures (c_1, c_2, ..., c_n). These crops must be irrigated daily using a total quantity of water Qt per day (in m^3).

Each crop has two important parameters: a minimum quantity of water necessary for the agricultural needs of the crop and a maximum quantity that must not be exceeded. These minimum and maximum quantities (in m^3/m^2) are respectively represented by the vectors

$Q_{min}=\{Q_{min1}, Q_{min2}, \ldots, Q_{minn}\}$ and $Q_{max}=\{Q_{max1}, Q_{max2}, \ldots, Q_{maxn}\}$.

The problem to be solved is the following: what will be the quantities Q_i which will have to be allocated daily to each culture C_i such that: $\sum_1^n Qi \leq Qt$ and $Qmin_i \leq Q_i \leq Qmax_i$

Methodology: PSO solution

The problem of managing the irrigation system with the aforementioned constraints is an optimization problem that can be solved using the PSO method by following the approach below (Figure 2);

Variables and Parameters Definition

Modeling the water distribution of an irrigation system using the Particle Swarm Optimization (PSO) algorithm can be an effective way to optimize irrigation efficiency while minimizing water consumption. To use PSO in this context, we start by defining certain variables and parameters detailed in Table 3.

Table 3. Modeling the irrigation system with the PSO algorithm

Parameters	Variable	Meaning	Unit	Value
PSO Parameters	P	Number of particles (candidate solutions)	Unit	Min = 20; Max = 50
	N	Number of iterations	Unit	Variable throughout the experiment (max = 100)
	c1	Cognitive learning coefficient	-	2 test values : 0.3 and 0.5
	c2	Social learning coefficient		2 test values : 0.1 and 0.3
	w	Inertia coefficient	-	3 test values : 0.5, 0.8 and 0.9
	r1, r2	PSO random variables	-	Random between 0 and 1
Irrigation system settings	D	Dimension of the research space (number of cultures)	Unit	10
	Qmin = [min1, min2, ..., min10]	Minimal water requirement	m³/m²	Random between 5 and 50
	Qmax = [max1, max2, ..., max10]	Maximum water requirement	m³/m²	Minimum water requirement incremented by a random value
	QT	Total amount of water available per day	m³	The sum of the minimum water requirement incremented by a random value
	X[p][i]	Quantity of water allocated by a particle p to a culture i	m3	Initialized during second phase of the process

Initialization

This phase consists of initializing all the aforementioned parameters in the table. But the most interesting thing in this phase remains the projection of the P particles randomly in the search space. In our problem, this consists of allocating quantities of water per particle to each crop. On the other hand, in this step, a random initial velocity is assigned to each particle. In our implementation, these velocities have all been initialized by 0.

The Objective Function

In PSO (Particle Swarm Optimization), the objective function, also called evaluation function or fitness function, is a mathematical function that defines the quality measure of candidate solutions (particles) in the search space. The objective of PSO is to find the best possible solution by optimizing this objective function.

The objective function is the heart of the PSO algorithm, because it guides particles in the search space to search for optimal solutions by adjusting their positions and velocities based on their own experience (pbest) and the collective experience of the group (gbest).

In the context of irrigation system management, the objective function consists of carrying out the following steps:

- For each particle n, calculate the total amount of water allocated to each crop i using X[n][i].
- Calculate irrigation efficiency and water consumption for each particle using the allocated water quantities. It is the distance between the total allocated quantity and the total available quantity.
- Define the objective function as a combination of irrigation efficiency (to be maximized) and water consumption (to be minimized).

Constraints and Evaluation

This step consists of updating the positions and speeds of the particles:

- Update particle velocities using the PSO formula.
- Update particle positions using the new velocities.
- Apply constraints to ensure that allocated water quantities remain within minimum and maximum requirements.

In the implementation carried out, this was achieved in two different ways:

Manual implementation: The positions and velocities are updated, at each iteration, using the formulas mentioned in the first part of this document. The best solution is obtained in global_best_position.

The ‘constraint’ function is a function which defines the constraints to be taken into consideration. The total water allocated to the crops by each particle should not exceed the total quantity. In addition, each quantity allocated by a particle n to a culture i must be between the minimum and maximum authorized value.

Python's pyswarm library: This is a library that provides an implementation of the PSO algorithm. This library provides a simple and easy-to-use interface for solving optimization problems with different algorithms available. In this work, we used the gbest PSO (Global Best PSO) algorithm.

Stopping Criterion

The call to the PSO algorithm is repeated until a stopping criterion is reached (for example, a maximum number of iterations or an objective function value sufficiently close to the optimum). Here, a maximum number of iterations has been set and is modified with each new test (See implementation and results sections). In addition, the program is launched continuously until the total value of allocated water is strictly lower than the total authorized quantity.

Choosing the Best Solution

Following several experiments detailed in the section below, we select the best solution found as the optimal distribution of water for the irrigation system.

Results and Discussion

In this section, several experiments will be carried out. First, we will set test data regarding the irrigation system. On these values, the previously detailed algorithm will be executed by changing each time the hyper parameters of the PSO method (inertia coefficient, cognitive and social coefficients, number of iterations and number of particles). At each test, the best solution and the best cost found – also called fitness score – will be mentioned.

Before starting the experiments, the test data concerning the context of the problem were set as follows:

- Number of crops: 10
- Minimum quantities of water required for crops: [40, 25, 18, 36, 34, 32, 26, 18, 40, 26]
- Maximum quantities of water required for crops: [50, 35, 28, 46, 44, 42, 36, 28, 50, 36]
- Quantity of water available: 395

Also, the PSO parameters were initially chosen as follows:

- Inertia coefficient w: 0.8
- Cognitive and social coefficients: 0.1
- Number of particles: 30
- Maximum number of iterations: 100

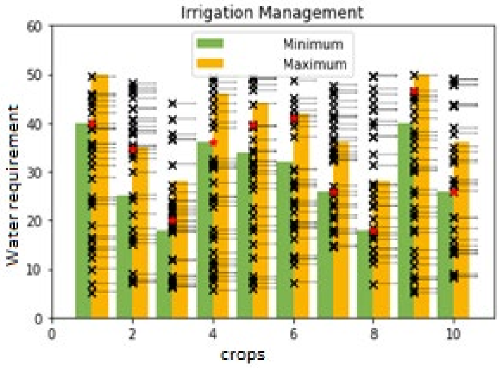
The results in manual implementation and using the pyswarm python package were obtained as presented in the Table 4.

The graphs below (Figure 3) represent respectively the best solution obtained (marked by red points) and the fitness score obtained in manual implementation of the PSO method.

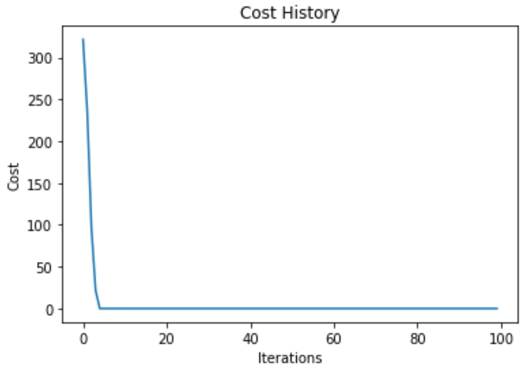
Experiment 1: Changing the inertia coefficient w

In this first test, all the PSO parameters kept their initial values, only the inertia coefficient w experienced several changes. In the Table 5 below, we show the results obtained with 3 different values using the python package Pyswarms.

The inertia coefficient is crucial in the PSO algorithm in balancing the exploration and exploitation. At w = 0.3, the particles are slowed rapidly which can lead to early convergence and hinder exploration of the solution space. In contrast, w = 0.9 encourages more exploration but could slow convergence. Our best cost result occurred at w = 0.9, indicating that in our irrigation optimization situation, favoring the global search provides marginal improvements in solution quality. In contrast, the difference with 0.5 and 0.3is still very small, showing how stable PSO is with respect to the inertia settings.



(a)



(b)

Figure 3. (a) The best solution marked with red points and (b) The cost obtained in manual implementation through iterations.

Table 4. The best solution, the best cost and the quantity of allocated water for manual implementation vs. using Pyswarms

	Manual implementation	PySwarms
Best solution	[40, 34, 20, 36, 39, 41, 26, 18, 46, 26]	[41, 31, 21, 41, 41, 38, 30, 20, 49, 32]
Best Cost	0.0011	0.00021
Allocated water quantity	328	354

Table 5. Experimentation 1 results : changing the inertia coefficient

	W=0.3	W=0.5	W=0.9
Best solution	[46, 29, 21, 39, 38, 41, 32, 23, 47, 28]	[41, 29, 24, 41, 43, 34, 33, 22, 47, 33]	[49, 34, 26, 39, 36, 39, 31, 26, 44, 30]
Best cost	0.0035	0.011	0.0024
Allocated water quantity	348	349	360

Table 6. Experimentation 2 results : changing cognitive and social coefficients

	C1 = 0.1 < c2 = 0.3	C1 = 0.3 > c2 = 0.1	C1 = 0.1 << c2 = 0.9	C1 = 0.9 >> c2 = 0.1
Best solution	[43, 28, 22, 44, 36, 39, 29, 24, 49, 29]	[46, 34, 23, 42, 38, 36, 32, 26, 48, 30]	[46, 27, 18, 41, 36, 34, 33, 27, 44, 32]	[43, 26, 26, 38, 40, 35, 26, 20, 41, 34]
Best cost	0.0029	0.09	0.61	0.001
Allocated water quantity	347	361	343	316

Table 7. Experimentation 3 results : changing the number of iterations

	NBR=50	NBR=200	NBR=500
Best solution	[43, 33, 18, 40, 40, 37, 28, 24, 47, 33]	[44, 34, 24, 37, 36, 38, 29, 21, 43, 34]	[41, 34, 24, 43, 42, 40, 28, 22, 40, 30]
Best cost	0.67	0.008	0.89
Allocated water quantity	347	346	348

Experiment 2: Changing cognitive and social coefficients (c1 and c2)

In this second test, all the PSO parameters kept their initial values (w=0.8), only the cognitive and social coefficients underwent changes. Four scenarios were considered apart from the case where c1 = c2 treated initially. In the Table 6, we show the results obtained using the python package Pyswarms.

C1 and C2 are parameters that control how strongly a particle will follow its own best-known position (c1) or how strongly it will seek the best-known position in the group (c2). With c1 >> c2, particles mostly explore all by themselves, which can result in less than optimal solutions. On the contrary, the c2 >> c1 could get stuck at local optima prematurely. Notably, lower (and in general reasonable) cost corresponded to c1 = 0.9 and c2 = 0.1, meaning that self-exploration indeed facilitated the particle to progress towards exploring different yet decent water allocation for filling the fragile resources.

Experiment 3: Changing the number of iterations

In this test, all PSO parameters kept their initial values (w=0.8 and c1=c2=0.1). We only varied the number of maximum iterations. In the Table 7 below, we show the results obtained using the python package Pyswarms for 3 different values.

Higher number of iterations means particles are allowed to roam in the search space longer, and that should lead to better solution. However, after some point, the quality-wise degrade because of oscillations or overfitting to non-optimal areas. 200 iterations generated the best cost, providing a satisfactory trade-off between computation time and performance. However, 500 iteration results performed less well than 200 iterations; this could indicate some overtraining which could lead to diminishing fitness due to either stagnation in search space or noise accumulation in search.

Table 8. Experimentation 4 results : changing the number of particles

	P= 10	P=50	P=80
Best solution	[46, 27, 26, 36, 42, 37, 31, 22, 48, 33]	[41, 29, 24, 38, 37, 40, 33, 21, 41, 34]	[42, 26, 26, 41, 40, 40, 33, 20, 40, 27]
Best cost	0.49	0.0004	0.29
Allocated water quantity	352	344	339

Table 9. Experimentation parameters of each optimization algorithm

Algorithm	Parameters	Values
PSO	Number of Particles	30
	Number of iterations	100
	Inertia	0.8
	Coefficients c1 and c2	0.1
	r1, r2	Between 0 and 1
GA	Population size	50
	Number of generations	200
	Crossover rate	0.8
	Mutation rate	0.05
	Selection method	Tournament (k=2)
	Elite breeders retained	2 best individuals
ACO	Number of ants	30
	Number of iterations	100
	Alpha (α) – pheromone	1.0
	Beta (β) – heuristic	3.0
	Rho (ρ) – evaporation	0.2
	Q – Deposition intensity	10
DE	Population size	60
	Number of generations	200
	Mutation factor (F)	0.7
	Crossover rate (CR)	0.5
	Mutation strategy	DE/rand/1/bin

Table 10. The experimentation 5 results : Comparing PSO to other optimization algorithms

Algorithm	Best Cost	Allocated Water Quantity	Remarks
PSO	0.00021	354	good convergence, easy to configure, fast
GA	0.0012	351	Slow convergence, sensitive to operators
ACO	0.0009	348	good exploration, time-consuming
DE	0.00019	353	Very good accuracy, but unstable if badly configured

Experiment 4: Changing the number of particles

In this last test, all the PSO parameters kept their initial values (w=0.8 and c1=c2=0.1, max iterations = 100). We only varied the number of particles. In the Table 8 below, we show the results obtained using the python package Pyswarms for 3 different values.

The population diversity in each iteration depends on the number of particles. A low number (e.g., 10) restricts the exploration and lessens the possibility for segmentation into local optimality and a too high number (e.g., 80) increases the computation without special-needs in the enhancement. The best cost obtained was 50 particles with a water allocation close to the goal. This suggests moderate swarm sizes are best for problems involving resource allocation constraints, such as irrigation scheduling, particularly when real-time responsiveness is preferred.

Experiment 5: Comparison with other similar algorithms

To evaluate the effectiveness of our PSO-based irrigation management approach, we conducted a comparative study using the same dataset and constraints with three other well-known metaheuristics: Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Differential Evolution (DE). Before diving into the details of the results obtained, here are the precise parameters used for each algorithm (see Table 9).

All algorithms respect bound and sum constraints thanks to:

- A penalty function integrated into the fitness for GA
- Manual reinitialization or repair for ACO
- Filtering or projection for DE

The Table 10 shows the results obtained for each algorithm

PSO and DE performed better than the GA and ACO in cost function and in allocation accuracy. Although the DE achieved a bit lower value for cost function (0.00019), PSO was able to converge faster, and provided easier parameter tuning making it a better choice for real-time and collective irrigation scenarios. ACO was computationally most costly and needed more iterations, however gave reasonable solutions. The performance of GA was inconsistent as it is sensitive to crossover and mutation rates. The results emphasize both the robustness and practicality of PSO across equitable and participatory irrigation systems.

Table 11. Comparative analysis of irrigation approaches

Method	Precision	Adaptability	Cost	Infrastructure needed	Collective USe
PSO-based Optimization	High	High	High	Low	Yes
Fuzzy Logic	Low	High	Low	Low	No
Internet of Things (IoT)	Medium	Medium	Medium	Medium	No
Traditional/Manual Scheduling	Low	Very high	Low	None	Yes

Comparative Analysis of PSO-based irrigation with traditional and smart approaches

In this section, a comparison of the proposed PSO-based approach is provided with the conventional irrigation systems and intelligent ones. The aim is to delineate the practical advantages, disadvantages, and contextual appropriateness of each method, particularly for smallholder farmers in resource-poor settings.

Recent developments in smart irrigation, such as rule-based control, fuzzy logic, and IoT-cloud-based solutions provide different levels of accuracy, complexity, and accessibility (Benzaouia et al., 2023; Et-taibi et al., 2024; Ikidid et al., 2021; Morchid et al., 2025; Rehman et al., 2024). However, few of these solutions explicitly treat collective water management or equity-based allocation, which are within the purview of this work.

A comparative summary of the PSO-based irrigation method vs. other popular smart irrigation methods is listed in Table 11. In contrast to traditional rule-based or fuzzy systems, PSO exhibits dynamic adaptability at low computational costs. In addition, the majority of smart systems tend to prioritize personal optimization, while our solution focuses on community fairness and social equity. IoT-based cloud systems can get similar results, but they demand expensive infrastructure and enable access that are still barriers in many rural areas. On the contrary, our method is optimization-performance based yet accessible and socio-economic inclusive.

This comparative analysis clearly shows that PSO is a reliable, flexible, and low-cost optimization technique for optimizing irrigation water allocation problem. By contrast, PSO can adapt its methods dynamically according to crop-specific constraints and achieves more efficient use of resources compared with conventional or manual scheduling or rule-based systems. PSO requires little expert involvement once parameters are defined, as opposed to fuzzy logic systems, which need careful semantic rules and other calibrations.

IoT systems can offer accuracy through real-time sensor data and remote control, but this often comes alongside expensive infrastructure and high energy use — which may not be sustainable or attainable for many smallholder farmers. And most of these smart systems are individually actionable, not participatory or population based solutions.

In contrast, the PSO methodology discussed in this work directly encourages democratized, collective irrigation through a balance of technical optimization and equitable social justice. This is particularly appropriate for such context where water is too scarce, and social glue is required in order to avoid conflict and encourage sustainability.

Conclusion

The application of machine learning in irrigation offers significant opportunities to improve water use efficiency and reduce costs for small-scale farmers. By adopting a collective and participatory approach, we can not only optimize crop irrigation, but also promote democratic water management, guaranteeing equitable access to this vital resource.

The socio-economic advantages of such an approach are multiple. First of all, it makes it possible to optimize water use by adapting irrigation needs to the specificities of each crop, thanks to machine learning systems. Second, it promotes solidarity between farmers by encouraging the pooling of resources and the equitable distribution of water, which can help strengthen community ties and reduce inequalities.

Furthermore, this approach can also have a positive impact on the social economy by stimulating agricultural productivity and improving the income of small farmers. By reducing irrigation costs, it allows farmers to invest in other areas, such as improving agricultural infrastructure or crop diversification, which can contribute to the economic resilience of rural communities.

In general, the results obtained in our study confirm the robustness and adaptability of the PSO algorithm with respect to all the parameter configurations. Despite some variations in performance, PSO consistently provided near-optimal allocations of water with minimal violations of constraints. This complexity suggests practical applicability in real-world irrigation systems where environmental and technical variation is great.

The proposed PSO-based irrigation optimization system is beneficial for small-scaled farmers in several ways. And first, it cuts down decision-making complexity, automating daily water allocation according to real crop requirements. Second, the system is flexible and can run on inexpensive devices, which is ideal for farmers with little technological expertise. A clear win in irrigation performance means lower costs to pump and enhanced resilience to farmers operating in water-limited modes. In addition, the collective and participatory policies of the system improves trust, distribution and in farmer communities the social cohesion. This tackles technical challenges as well as socio-political tensions characteristic in rural areas reliant on irrigation.

To fully exploit the potential of smart, collective and participatory irrigation, it is essential to put in place favorable public policies that encourage the adoption of these new technologies and support small farmers in their transition to more sustainable agricultural practices. Furthermore, further research is needed to assess the long-term impact of these approaches on the environment, society and the economy, in order to best guide policy decisions and future investments in this area.

In conclusion, intelligent, collective and participatory irrigation offers many opportunities to improve the sustainability of agriculture, strengthen social cohesion and stimulate the local economy. By investing in these new approaches, we can help create a more sustainable and equitable future for all.

Declarations

The authors declare that they have no conflict of interest regarding the publication of this article. All data are included in the manuscript or supplementary files.

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