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APPLICATION OF BACK-PROPAGATION ARTIFICIAL NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION METHODS IN SPRINKLER OPTIMIZATION

Zakaria Issaka[a*]

[a] Department of Agricultural Engineering, Tamale Technical University, P. O. Box 3 E/R, Tamale, Northern Region, Ghana, e-mail: issakazak@gmail.com, ORCID 0000-0002-8629-0656

Corresponding author: e-mail: issakazak@gmail.com

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ABSTRACT

The aim of this paper was to analyze the primary and secondary order of influencing factors and to establish a BP neural network prediction model with different hydraulic performance indicators. Particle swarm optimization algorithm was used to test for the optimal hydraulic performance of the nozzle and validated by experiment. The orthogonal design covered the 200–300 kPa range, while the PSO algorithm selected 540 kPa based on the full dataset. The sprinkler was raised at a height of 1.4 m from the ground level in a square configuration. The optimal parameter combination for the square layout achieved higher uniformity and controlled maximum kinetic energy relative to the average sprinkling intensity. Results from the experiment gave 4.71 $mm \cdot h^{-1}$, 83.28% and 0.0078 $W \cdot m^{-2}$ for average sprinkler intensity, CU and maximum kinetic energy, respectively. Compared with the range-analysis-based scheme, the optimized configuration reduced average irrigation intensity while improving uniformity and kinetic energy performance. The maximum error between experimental results and optimization results was 3.29%, indicating that the optimization model is feasible and reliable. This study proposes a practical optimization framework for the design and operation of sprinkler irrigation systems.

Introduction

Sprinkler irrigation is widely applied in modern agriculture due to its flexibility, efficiency, and adaptability to diverse field conditions. Within sprinkler systems, the nozzle is a critical component, as its hydraulic performance directly affects spray quality, irrigation uniformity, and operational efficiency (Yuan et al., 2015; Yan et al., 2007; Kang et al., 2004). Therefore, systematic evaluation of nozzle-related parameters is essential for improving sprinkler hydraulic performance.

Previous studies have examined the effects of nozzle structural characteristics, operating pressure, and configuration on hydraulic performance. Research on full-jet and rotary nozzles

has shown that variations in key geometric and operational parameters can significantly influence sprinkler range, water distribution uniformity, and sprinkler intensity (Yuan et al., 2006; Zhu et al., 2015; Liu et al., 2013; Pan et al., 2016). In addition, studies have demonstrated that droplet kinetic energy is closely linked to soil surface damage, runoff formation, and erosion risk, highlighting the need to consider energy-related indicators alongside traditional uniformity metrics (Bubenzer et al., 1971; Han et al., 2013; Liu et al., 2009; Yuan, 2004).

Although these studies have provided valuable insights into individual influencing factors, most investigations have focused on isolated parameters or single performance indicators. The hydraulic performance of a sprinkler nozzle is, however, governed by multiple interacting factors, including nozzle geometry, rotation characteristics, operating pressure, installation height, and environmental conditions, resulting in complex and nonlinear relationships among performance indicators.

To address the complexity arising from these interacting factors, data-driven and metaheuristic optimization methods have gained increasing attention in recent years. Artificial neural networks (ANNs) and particle swarm optimization (PSO) techniques have been increasingly applied to complex engineering problems due to their ability to model nonlinear systems and solve multidimensional optimization tasks (Bülbül, 2023; Hu et al., 2023; Xia et al., 2022; Ge et al., 2021). The PSO has proven particularly effective in optimization problems across various fields, including hydraulic and agricultural engineering (Czarnecki et al., 2021; Yan et al., 2011). Applications of PSO in sprinkler irrigation research have demonstrated its potential for optimizing emitter structures and spray characteristics (Liu et al., 2013; Wei et al., 2020). However, existing studies have predominantly addressed specific performance objectives or high-pressure systems, with limited emphasis on medium- and low-pressure impact sprinklers operating under varying installation configurations.

Consequently, integrated studies that simultaneously address multiple hydraulic performance indicators under realistic operating conditions remain limited. In practical irrigation system design, objectives such as uniform water distribution, controlled sprinkler intensity, and reduced droplet kinetic energy must be considered together rather than independently. The present study addresses this gap by combining a BP neural network with particle swarm optimization to analyze and optimize the hydraulic performance of an impact sprinkler, providing a multi-objective framework applicable to sprinkler-irrigated fields under controlled operating conditions.

The objectives of this study were to (i) identify the main adjustable parameters affecting the hydraulic performance of an impact sprinkler, and (ii) determine the relative importance of these parameters by developing a BP neural network prediction model for multiple hydraulic performance indicators.

An impact sprinkler equipped with a 6 mm nozzle was evaluated under different installation heights (0.8, 1.1, and 1.5 m), combined spacing configurations (R, 1.3R, and 1.6R), and operating pressures (200, 250, and 300 kPa). The hydraulic performance indicators considered in the full-factor experiment included average sprinkler intensity (Y_1), combined sprinkler uniformity coefficient (Y_2), and kinetic energy intensity (Y_3).

A three-layer BP neural network was used to create an optimal model for the hydraulic performance of the sprinkler. The study is limited to indoor laboratory conditions without

wind influence. Therefore, it is recommended the experiment be repeated under field conditions to validate and ensure direct applicability of the results obtained. Nevertheless, the proposed methodology can be applied to similar multi-objective optimization problems in practical sprinkler system design.

METHODOLOGY

Experimental design

Hydraulic performance experiments were conducted in wind-free indoor sprinkler test space. Impact sprinkler with nozzle of 6 mm was selected as the test sprinkler. The sprinkler was installed at a height of 1.4 m and operated under working pressures ranging from 200 to 300 kPa, as defined by the orthogonal experimental design. Nozzle working pressure was monitored using a precision pressure gauge with an error margin of 0.4, positioned 25 cm from the nozzle. The flow rate was measured by an electromagnetic flowmeter with a precision of 0.5. Sprinkler water distribution was measured using rain gauges with an opening diameter of 0.2 m and a height of 0.6 m, arranged at 1 m intervals along three radial lines. Data averaging along two radial lines was used to represent the various radial lines around the circle due to the absence of wind within the irrigation space. As can be seen in Figure 1, the rain gauges were placed every 1 m along a single radial line. This setup aimed to acquire more precise wetted radius data. The experimental protocol commenced after 10 minutes of stable operation, with a testing duration of 1 hour. The water application rate at different points was measured during this time. Each test was repeated three times, and mean values were used for analysis. Figure 1 presents the layout of cans around sprinkler in the indoor laboratory.

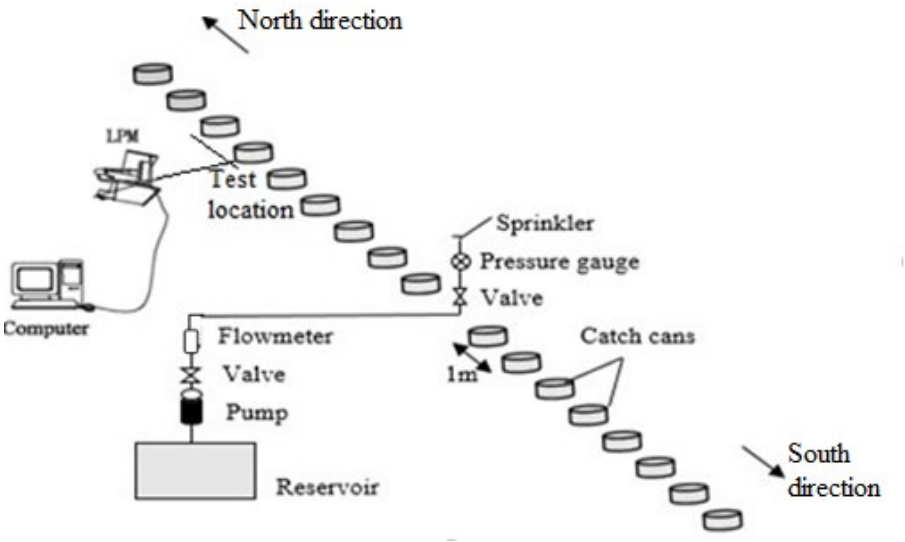

Figure 1. Layout of catch cans around the sprinkler in the indoor test

Table 1 presents levels of parameters adopted in the study.

Table 1.
Levels of the study parameters

Level	Sprinkler working pressure A/Kpa	Sprinkler installation height B/m	Installation pitch (R is the sprinkler range)/m
1	200	0.8	R
2	250	1.1	1.3R
3	300	1.5	1.6R

The water droplets sizes velocity including the corresponding number of water droplets were measured by a Laser Precipitation Monitor (LPM) developed by ThiesClima, Germany. When spraying water droplets through a set of parallel laser bands generated by the laser optical source of the laser raindrop spectrometer, the receiver can measure the amplitude and time of the voltage signal attenuation caused by the crossing particles, thereby deriving the size and falling speed of the water droplets (Wang, 2011; Schoenhuber and Randeu, 2000). The measured particle size range was 0.125~8.0 mm; the particle velocity ranged from 0.2~20.0 $m \cdot s^{-1}$. To reduce the experimental measurement error, the normal distribution model "3 rule" was used in the processes (Wang et al., 2017). After the nozzle was stable, the test was started. Each experiment was repeated 3 times. The experiments were carried out in accordance with the national standard GB/T22999-2008 "Rotary nozzle" and the national standard GB/T 27612.3-2011 "Water distribution uniformity and Test method" Lao and Han (2010).

Performance indicators

Average sprinkler intensity

To prevent surface runoff and soil erosion, sprinkler irrigation intensity should remain below the soil infiltration capacity. Average sprinkler intensity represents the mean irrigation intensity over the entire wetted area and is calculated using Equation (1).

$$\overline{\rho} = \frac{\sum_{i=2}^{n} \rho_i}{n} \tag{1}$$

where:

$\bar{p}$ – the average sprinkling intensity, ($mm \cdot h^{-1}$)
n – represents the number of points of the same area,
p_i – the point area of sprinkler intensity, ($mm \cdot h^{-1}$)

Combined sprinkler uniformity coefficient

Sprinkler uniformity refers to the uniformity of water distribution on sprinkler area, which has a decisive influence on crop yield, and is an important indicator to measure sprinkler irrigation quality. Lao and Han (2010) and Bautista-Capetillo et al. (2012) indicated that the uniformity is expressed by the Christiansen uniformity coefficient (CU), which can better

reflect the deviation of the water distribution and the average sprinkler intensity in the spray field. Square arrangement is a widely embraced layout in irrigation planning due to its convenience in pipeline design and practical engineering considerations (Issaka et al., 2018). In this study, a mathematical superposition was implemented by arranging four sprinklers (marked as bullets) in a square configuration and adjusting the spacing factors from R to 1.3R with an increment of 0.1R (where R represents the wetted radius of the sprinkler). In the simulation, four sprinklers were mathematically juxtaposed at a maximum spacing coefficient of 1.4R, and the combined uniformity was determined using Matrix Laboratory (MATLAB) software program. The combined CU of was calculated using Equation (2) (Gao et al., 2022).

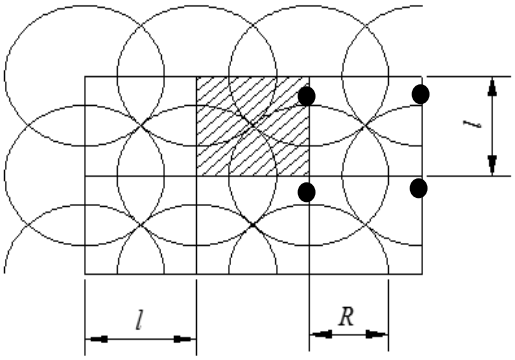

Figure 3. Schematic diagram of sprinkler in square arrangement.

$$CU = \left(1 - \frac{|\Delta h|}{h}\right) \times 100\% \tag{2}$$

$$h = \frac{\sum_{i=1}^{n} h_i}{n} \quad |\Delta h| = \frac{\sum_{i=1}^{n} |h_i - h|}{n} \tag{3}$$

where:

CU – sprinkler uniformity coefficient, (%)

h_1 – is the average value of N/4 minimum water depth measuring points, (mm)

h_2 – is the average sprinkler intensity on the sprayed area, (mm)

Kinetic energy intensity

The kinetic energy of sprinkler irrigation is an important parameter to characterize the precipitation energy distribution in sprinkler irrigation system, predict surface runoff and soil erosion (Yan et al., 2011). The intensity of kinetic energy depends on the diameter, velocity and sprinkling intensity of the sprayed water droplets, indicating the amount of kinetic energy at the spray area per unit time (Burillo et al., 2013). The calculation formula is given in Equation 4.

$$S_{pj} = \frac{\sum_{i=1}^{n} \frac{1}{12} \pi d_i^3 \rho_\omega v_i^2}{1000 \sum_{i=1}^{n} \frac{1}{6} \pi d_i^3} \frac{\rho_j}{3600} \quad (4)$$

where:

Spj – is the kinetic energy of the spray kinetic energy to the distance *j* of the nozzle, ($W \cdot m^{-2}$)

hj – is the sprinkler intensity at the measuring point of the nozzle at different distances, ($mm \cdot h^{-1}$)

j – is the measuring point at different distances from the nozzle of the sprinkler, (mm)

PSO parameter optimization

In the particle swarm optimization framework, each particle represents a potential solution in the search space. Particles are initialized with random positions and velocities, which are iteratively updated based on individual best positions and the global best solution, enabling efficient exploration of the solution space.

The ANN-PSO model was implemented in MATLAB 2013a. Using the highest number of iterations, the input parameters was optimized. A swarm size of 10 randomly initiated particles and 50 iterations were considered as the maximum and were selected as 0.8, 1.05 and 1.05 respectively.

Velocity Update*:* At each iteration, a particle's velocity was adjusted using Equation (5):

$$v[t+1] = w * v[t] + c_1 * r_1 * (pBest[t] — x[t]) + c_2 * r_2 * (gBest[t] — x[t]) \quad (5)$$

Position Update*:* Following the velocity update, the particle's position was updated to *x[t+1] = x[t] + v[t+1]*, moving it closer to the optimal solution based on the newly calculated velocity.

Where *w* is inertia weight, c_1 is cognitive coefficient, and c_1 is social coefficient, which measures the tendency of nodes (water droplets) to connect or cluster with similar nodes.

Inertia Weight (w) Update*:* is the most important parameter for the convergence of PSO, and was updated using Equation (6);

$$w = wmax - (wmax - wmin) \times k/Maxite. \quad (6)$$

where:

Maxite – is the maximum iteration fixed,

k – is the current iteration in operation.

At the beginning of the training, the value of the weight was reduced quickly to find the optimal global value but when around the global optimum the weight value was reduced slowly.

Since MATLAB PSO algorithm runs as a minimization approach, therefore the objective function i.e. maximization of RMSE was formulated as equivalent minimization problem given as:

$$\text{Objective function} = \frac{\text{minimise}}{X \epsilon X^T} \left(\frac{1}{FX}\right) \tag{7}$$

where:

$X = [X1, X2, X3]^T$ signifies the decision solution vector and

$F(X)$ – is the output from the ANN. The upper and lower bounds are given as $1 \leq X_1 \leq 3$, $10 \leq X_2 \leq 50$ and $0.27 \leq X_3 \leq 0.31$. The swarm size of 10 randomly initiated particles and 50 iterations were considered as the maximum. Each acceleration coefficients value (c_1 and c_2) and the inertia weight parameter (w) were selected as 1.05 and 0.8, respectively.

Check stopping criteria: if $k \leq Maxk$ then *Goto* Equation 6 else end if Print G*k* and update ANN weights and biases.

Results and discussion

Test results and analysis of variance

The orthogonal table was selected for the range analysis, irrespective of the interaction between the factors. In sprinkler hydraulics, interactions (e.g., pressure × installation height) may be significant, however in this study only the main effects were analyzed. MATLAB was used to compile the radial water distribution data of the test sprinkler into the grid data calculation software. The software was further used to establish a grid point within the spray nozzle range, and the measured sprinkler application depth data was used to make the spline of the grid point to the nozzle. Interpolation was used to find the water depth of each grid point, and then obtain the combined sprinkler water distribution data according to the different installation spacing of the sprinkler, and calculate the corresponding average sprinkler intensity and combined CU. Table 1 shows the factor level and test plan results.

The three indicators of the sprinkler irrigation hydraulic performance were analyzed by the range difference. The average sprinkler intensity was A1B3C3, the square combination arrangement uniformity coefficient was A2B1C1 and the maximum kinetic energy intensity was A1B2C1. The optimal parameter combinations differed across the three performance indicators. A configuration optimized for one performance indicator did not necessarily yield optimal results for the remaining indicators. To identify a parameter combination that provides balanced performance across all evaluation indices, each impact factor was analyzed individually according to the following.

Nozzle working pressure A: For the square uniformity coefficient, the maximum difference of A is the largest influencing factor, and A2 was the best, however for the average sprinkling intensity and maximum kinetic energy intensity, the difference of A was not the largest. It is better to take A, however, according to the principle of comprehensive balance law, it is best to select A2.

Nozzle installation height B: For the maximum kinetic energy intensity, B had the largest difference, which had the largest influencing factor. It is best to take B2, but the difference between B and the average sprinkling intensity is the smallest. It is the least influential factor. It is best to take B1 and B3 respectively. According to the principle of comprehensive balance method, it is best to choose B2.

Table 2.
Test plan and result analysis

Factor / Test number		1 A	2 B	3 C	Test results of each evaluation index		
					Average sprinkler intensity Y1 (mm/h)	Square arrangement uniformity coefficient Y2 (%)	Maximum kinetic energy intensity Y3 ($W \cdot m^{2)}$)
1		1	1	1	7.67	67.44	0.0118
2		1	2	2	2.82	64.46	0.0074
3		1	3	3	2.75	66.41	0.0034
4		2	1	2	6.52	82.27	0.0049
5		2	2	3	3.48	70.69	0.0046
6		2	3	1	8.82	85.91	0.0102
7		3	1	3	2.16	71.18	0.0032
8		3	2	1	13.01	80.42	0.0122
9		3	3	2	2.79	57.15	0.0045
Average sprinkler intensity	K_1	13.24	16.35	29.5			
	K_2	18.82	19.31	12.04			
	K_3	17.96	14.36	8.39			
	R	5.58	4.95	21.11			
	Excellent solution	A_1	B_3	C_3			
Square arrangement uniformity coefficient	K_1	198.31	220.89	233.77			
	K_2	238.84	215.57	203.88			
	K_3	208.75	209.47	208.28			
	R	40.53	11.42	29.89			
	Excellent solution	A_2	B_1	C_1			

		Column number		
		1 A	2 B	3 C
Maximum kinetic energy intensity	K_1	0.0226	0.0199	0.0342
	K_2	0.0197	0.0242	0.0168
	K_3	0.0199	0.0181	0.0112
	R	0.0029	0.0061	0.023
	Excellent solution	A_1	B_2	C_1

Installation spacing C: For the three evaluation indicators, the difference of C was not the largest, it is not the strongest influencing factor, and it is a less important factor. For the maximum kinetic energy intensity and the uniformity coefficient of the square arrangement, C takes C1. Best, and for the average sprinkler intensity, C is the best C3. According to the principle of "the minority obeys the majority", C takes C1 best. A comprehensive analysis of the influence of factors on each evaluation index shows that the resulting optimal parameter combination was A2B2C1.

BP neural network structure design and fitting

In this paper, ANN+PSO three-layer BP neural network was used to create an optimal model for the hydraulic performance of the sprinkler. Three topological structure variables were selected: the working pressure, the installation height and the combined spacing of the sprinkler. The number of neurons in the input layer was three, of which x_1 was the working pressure of the nozzle, x_2 was Installation height and $x3$ was the combined spacing. The objective function was the maximum kinetic energy intensity, the number of output neurons and Equation (8) of the number of neurons in the hidden layer is given as:

$$P = \sqrt{n + q} + z \tag{8}$$

where:
P – is the number of hidden layer nodes,
n – is the number of input layer nodes,
q – is the number of output layer nodes, and
Z – is the empirical value (1≦Z≦10).

The number of hidden layers was 7 by debugging network performance. The maximum kinetic energy intensity and the neural network model of the external configuration parameters of each nozzle were 3-7. The network topology of the BP neural network is shown in Figure 2.

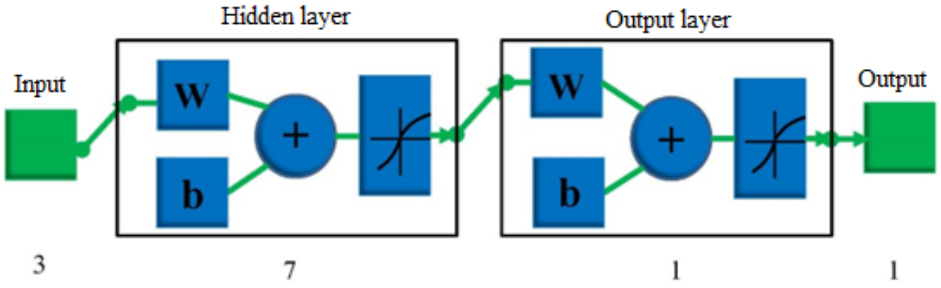

Figure 2. BP neural network structure diagram

Using MATLAB to write BP neural network-related software, the transfer function between each hidden layer adopts single-level Sigmoid function, and the maximum kinetic energy intensity and the objective function between each influencing factor are.

$$Y = F(X) = F[V \cdot F(W \cdot X + \theta_1) + \theta_2] \tag{9}$$

where:

f(*X*) – is a single-stage Sigmoid function,
X – is the input vector value, *X* = [*X1, X2, X3*] *T*
Y – is the output vector value, *Y* = [*y1*]

F(X) is a function between the input value and the output value. *θ1* and θ2 are the thresholds between the hidden layer and the output layer, respectively, W is the weight matrix between the input layer and the output layer, and V is hidden. A matrix of weights between the layer and the output layer. The data is normalized by MATLAB's own function, Mapminmax. The normalized interval is [0,1]. The number of iterations and initial learning efficiency of the network are 100 times and 0.08 respectively. The training algorithm uses Bayesian regular algorithm. When the output error satisfies 0.0001, the network meets the training requirements, and the weight matrix WT of the input layer and the output layer is as follows:

$$\begin{bmatrix} 0.0571 & 0.2298 & 0.0620 & -0.0668 & 0.0498 & 0.0473 & 0.0525 \\ 0.0151 & -0.0587 & 0.0212 & -0.0335 & 0.0094 & 0.0080 & 0.0112 \\ 0.1864 & 0.6636 & 0.2120 & -0.2495 & 0.1551 & 0.1455 & 0.1659 \end{bmatrix}$$

The threshold value of the hidden layer θ1 = [0.0138 0.4020 0.0188 - 0.0255 0.0083 0.0069 0.0101] T, V = [-0.1989 - 0.7941 - 0.2261 0.2652 - 0.1654 - 0.1552 - 0.1770], θ2 = [0.0058].

When the objective function is a square arrangement uniformity coefficient and average sprinkling intensity, after BP neural network construction and parameter configuration, the weight matrix W of the input layer and the hidden layer of the BP neural network model after training is obtained.

$$\begin{bmatrix} 0.0573 & 0.0985 & -0.0383 & -0.0290 & 0.0112 & 0.0442 & 0.0268 \\ 0.0081 & 0.0112 & -0.0047 & -0.0034 & 0.0013 & 0.0057 & 0.0032 \\ -0.1094 & -0.1953 & 0.0750 & 0.0571 & -0.0220 & -0.0803 & -0.0525 \end{bmatrix}$$

$$\begin{bmatrix} 0.0573 & 0.0985 & -0.0383 & -0.0290 & 0.0112 & 0.0442 & 0.0268 \\ 0.0081 & 0.0112 & -0.0047 & -0.0034 & 0.0013 & 0.0057 & 0.0032 \\ -0.1094 & -0.1953 & 0.0750 & 0.0571 & -0.0220 & -0.0803 & -0.0525 \end{bmatrix}$$

The threshold θ1 of the hidden layer is [0.0140 0.0197 -0.0133 -0.0057 0.0022 0.0074 0.0052] T, [0.0140 0.0197 -0.0133 -0.0057 0.0022 0.0074 0.0052] T, respectively. The weight matrix V of the hidden layer and the output layer are [0.0894 0.0133 -0.1061 -0.0103 0.0137 0.1074 0.0336], [0.0894 0.0133 -0.1061 -0.0103 0.0137 0.1074 0.0336], respectively. The threshold θ2 of the output layer is [0.0058] and [0.1121], respectively.

When the objective function is the maximum kinetic energy intensity, the square arrangement uniformity coefficient and the average sprinkler intensity, the residual values of the BP neural network model and the experimental values are shown in Fig. 3(a)(b)(c), respectively. The correlation coefficients R were 0.94 ($p<0.01$), 0.91 ($p<0.05$), and 0.93 ($p<0.01$),

respectively. The root mean square error RMSE was 0.004 W·m^2, 14.67%, and 3.71 mm/h, respectively. It indicates that the fitting degree and accuracy of BP neural network are better. The BP neural network fitting function can more accurately reflect the functional relationship between each experimental factor and the experimental target value.

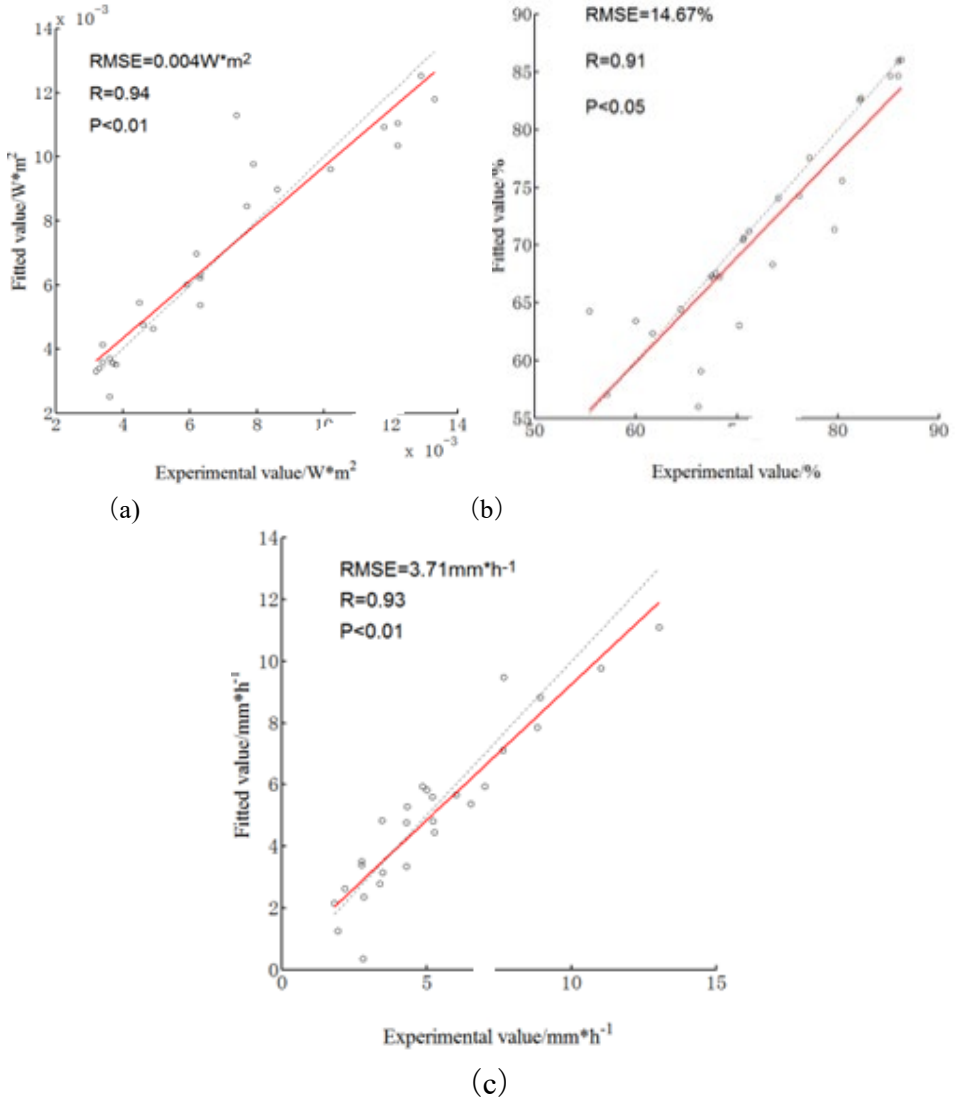

Figure. 3 Comparison of BP neural network fitting value and experimental value

Global optimization of nozzle hydraulic performance model

Taking the trained BP neural network model as the objective function, the particle swarm algorithm multi-objective search algorithm was used to optimize; (1) the sprinkler intensity, (2) square arrangement uniformity coefficient, (3) maximum kinetic energy intensity and (4) solve the network input to obtain the optimal value. From 50 different random particle positions $X(0)$, the velocity was initialized to 0. The particle fitness value refers to the established nozzle hydraulic performance model. There were three fitness for each individual, namely the average sprinkler intensity of the nozzle, the uniformity coefficient of the square arrangement and the maximum kinetic energy intensity. According to the upper and lower limits of each factor level of the test design, the constraints that the individual must meet are;

$$\begin{cases} 100 < \mathrm{x}_1 < 500 \\ 0.8 < \mathrm{x}_2 < 1.8 \\ 0.8\mathrm{R} < \mathrm{x}_3 < 1.8R \end{cases}$$

Particle velocity and position update must update particle velocity and position based on individual optimal particle position and global particle position.

$$V^{\mathrm{k}+1} = \omega V^{\mathrm{k}} + c_1 r_1 \left(P_{\mathrm{id}}^{\mathrm{k}} - X^{\mathrm{k}}\right) + c_2 r_2 \left(P_{\mathrm{gd}}^{\mathrm{k}} - X^{\mathrm{k}}\right) \tag{10}$$

$$X^{\mathrm{k}+1} = X^{\mathrm{k}} + V^{\mathrm{k}+1} \tag{11}$$

Where ω is the inertia weight; r_1 and r_2 are random numbers distributed in the interval [0,1]; k is the current number of iterations; k is the optimal particle position of the individual; P is the global optimal particle position; c_1 and c_2 are constant; V is the particle velocity; X is the particle position.

A multi-objective search algorithm was used to iterate 200 times to obtain a non-inferior solution set. When considering the priority order of the objective function as the square arrangement uniformity coefficient>maximum kinetic energy>average sprinkler intensity and the combined parameters under multi-objective optimization were obtained. The optimal combination parameters are the working pressure of the sprinkler was 540 kpa with 1.4 m installation height in a square arrangement R. The corresponding average sprinkler intensity, square combination arrangement uniformity coefficient and maximum kinetic energy intensity were 4.81 mm/h, 86.12%, and 0.0080 W·m^2, respectively. The algorithm of PSO is shown in Fig.3.

Model verification

To verify the reliability of the predicted regression model, the experiment was repeated three times according to the above-mentioned nozzle working conditions, and the experimental results were averaged. If the experimental values obtained by the experiment are close to the predicted values of the BP neural network model, it can be considered that established hydraulic performance prediction model is reliable. Table 3 presents comparative analysis of predicted and experimental values under multi-objective optimization conditions.

Table 3.
Predicted and experimental values under optimized conditions.

Hydraulic parameter	Predictive value		Test value		Error (%)	Difference between Scenario 1 and Scenario 2 (%)
	Scenario 1	Scenario 2	Scenario 1	Scenario 2	Scenario 2	
Average sprinkler intensity (mm/h)	4.83	4.81	4.79	4.71	2.08	1.67
Uniformity coefficient (%)	81.79	86.12	81.20	83.28	3.29	-2.56
Maximum kinetic energy (W/m^2)	0.0068	0.0080	0.0073	0.0078	2.50	-6.84

As observed, the predicted values of the three response indicators in the multi-objective optimization were close to the corresponding experimental values, the maximum and minimum errors were 3.29 and 2.08%, respectively. Comparative analysis of the optimal experimental scheme under the orthogonal experiment (Scheme 1) and the parameter configuration under the particle group multi-objective optimization (Scheme 2) showed that the corresponding average sprinkler intensity differed by 1.67%, the square arrangement uniformity coefficient differs by -2.56% and the maximum kinetic energy intensity differed by -6.84%. The predicted regression model of the three different hydraulic performances was suitable, and the obtained nozzle operating parameter configuration was better in the above hydraulic performance priority.

Conclusion

In this paper, orthogonal test was used to analyze the influence of nozzle working pressure, installation height, square arrangement spacing on the average sprinkler intensity, square arrangement uniformity coefficient and maximum kinetic energy intensity of the full jet nozzle. The following conclusions can be drawn:

1. For average sprinkler intensity, the most influential factor was combined spacing, followed by nozzle working pressure and installation height. In contrast, sprinkler working pressure had the greatest effect on uniformity, whereas installation height exerted the strongest influence on maximum kinetic energy intensity.
2. A BP neural network prediction model with average sprinkler intensity, square arrangement uniformity coefficient and maximum kinetic energy intensity was established. R2 of the three hydraulic performance prediction models established were 0.93, 0.98 and 0.90, respectively, and the prediction performance was better.

3. When prioritizing uniformity over kinetic energy and average sprinkler intensity, the optimal configuration consisted of a nozzle working pressure of 540 kPa, an installation height of 1.4 m, and square spacing R.

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Conflicts of Interest: The author declare no conflict of interest in this paper.
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References

Bautista-Capetillo C., Zavala M., Playán E. (2012). Kinetic energy in sprinkler irrigation: different sources of drop diameter and velocity. *Irrigation Science*, *30*(1), 29-41.

Bubenzer G. D., Jones B. A., Jr. (1971). Drop size and impact velocity effects on the detachment of soils under simulated rainfall. *Amer Soc Agr Eng Trans ASAE*, *14*(4), 0625-0628.

Bülbül M. A. (2023). Kuru fasulye tohumlarının çok sınıflı sınıflandırılması için hibrit bir yaklaşım. *J. Inst. Sci. Techn. 13*, 33-43.

Burillo G. S., Delirhasannia R., Playán E. (2013). Initial drop velocity in a fixed spray plate sprinkler. *Journal of Irrigation & Drainage Engineering*, *139*(7), 521-531.

Czarnecki S., Shariq M., Nikoo M., Sadowski Ł. (2021) An intelligent model for the prediction of the compressive strength of cementitious composites with ground granulated blast furnace slag based on ultrasonic pulse velocity measurements. *Measurement*, *172*, 108951.

Gao, F., Zhang, R., Zhu, D., et al. (2022). Hydraulic performance test and optimal working parameters of Teejet atomizing nozzle. *Journal of Agricultural Engineering*, *38*(22), 280-286.

Ge L., Li Y., Yan J., Wang Y., Zhang N. (2021). Short-term load prediction of integrated energy system with wavelet neural network model based on improved particle swarm optimization and chaos optimization algorithm. *Journal of Modern Power Systems and Clean Energy*, *4*(2), 1-12.

Han W., Cui L, Wu P. (2013). Calculation methods for irrigation uniformity with sprinklers spaced in regular triangle. *Transactions of the Chinese Society for Agricultural Machinery*, *44*(4), 99-107.

Hoła A., Czarnecki S. (2023). Random forest algorithm and support vector machine for nondestructive assessment of mass moisture content of brick walls in historic buildings. *Autom. Constr*, *149*, 104793.

Hu L., Yang Y., Tang Z., He Y., Luo X. (2023). Fcan-mopso: An improved fuzzy-based graph clustering algorithm for complex networks with multi-objective particle swarm optimization. *IEEE Transactions on Fuzzy Systems*, *2*(5), 1-16.

Issaka Z., Li H., Jiang Y., Tang P., Chen C., Darko R. O. (2018). Hydraulic performance characteristics of impact sprinkler with a fixed water dispersion device. I*nt J Agric & Biol Eng, 11*(6), 104–112.

Kang S., Cai H., Feng S. (2004). Technique innovation and research fields of modern agricultural and ecological water-saving in the future. *Transactions of the Chinese Society of Agricultural Engineering, 20*(1), 1-6.

Lao D. Q., Han W. T. (2010). Research on software for sprinkler water distribution dynamic simulation and spacing optimization. *Water Saving Irrigation, 2*(3), 1-12.

Liu C. J., Zheng J. Q., Wang K. Y. (2009). Prediction model for atomization performance of electrostatic spraying nozzle. *Transactions of the Chinese Society for Agricultural Machinery, 40*(4): 63-68.

Liu J. (2013). Experiments of Hydraulic Performance for Variable Complete Fluidic Sprinkler. *Transactions of the Chinese Society for Agricultural Machinery*, *44*(2), 75-79.

Pan T., Hong L., Chao C. (2016) Optimization and experiment of adjustable structural parameters for vertical impact sprinkler with working pressure. *Transactions of the Chinese Society of Agricultural Engineering*, *32*(20), 99-107.

Schoenhuber M., W.L., Randeu H. E. (2000). Field measurements of raindrop orientation angles, AP Milleneum Conf. Ant. Prop., Davos, Switzerland, 9-16 April.

Wang F., Dong Z., Wu Z. (2017). Optimization of maize planting density and fertilizer application rate based on BP neural network. *Transactions of the Chinese Society of Agricultural Engineering, 33*(6), 92-99.

Wang K. (2011). The detection and elimination of abnormal data for the precipitation observed by Parsivel precipitation particle spectrometer. *Journal of the Meteorological Sciences, 31*(6), 732-736.

Xia X., Song H., Zhang Y., Gui L., Xu X., Li K., Li, Y. (2022). A particle swarm optimization with adaptive learning weights tuned by a multiple-input multiple-output fuzzy logic controller. *IEEE Transactions on Fuzzy Systems*, *1*(2), 1-15.

Yan H. J., Bai G., He J. Q. (2011). Influence of droplet kinetic energy flux density from fixed spray-plate sprinklers on soil infiltration, runoff and sediment yield. *Biosystems Engineering,110*(2), 213-221.

Yan H., Wang M., Yang X. (2007). Effect of bullet-shaped straightener on hydraulic performances in internal flow passage of the impact sprinkler. *Transactions of the Chinese Society for Agricultural Machinery*, 30(17), 109-116.

Yuan S., Hong L., Wang X. (2015) Status,problems,trends and suggestions for water-saving irrigation equipment in China. *Journal of Drainage & Irrigation Machinery Engineering, 33*(1), 78-92.

Yuan S., Zhu X., Li H. (2006). Effects of complete fluidic sprinkler on hydraulic characteristics based on some important geometrical parameters. *Transactions of the Chinese Society of Agricultural Engineering, 22*(10), 113-116.

Yuan X. H, Cheng W., Zhang Y. C. (2004). A survey on application of particle swarm optimization to electric power systems. *Power System Technology, 28*(19), 14-19.

Zhu X., Liu X., Liu J. (2015). Droplet kinetic energy distribution regulation of complete fluidic sprinkler. *Transactions of the Chinese Society of Agricultural Engineering, 31*(15), 26-31.

ZASTOSOWANIE SZTUCZNEJ SIECI NEURONOWEJ Z ALGORYTMEM WSTECZNEJ PROPAGACJI ORAZ ALGORYTMU OPTYMALIZACJI ROJU CZĄSTEK W OPTYMALIZACJI ZRASZACZY

Streszczenie. Celem pracy była analiza czynników pierwszego i drugiego rzędu, które wpływają na parametry pracy zraszaczy oraz opracowanie modelu predykcyjnego dla różnych wskaźników ich wydajności hydraulicznej bazującego na sztucznej sieci neuronowej BP. Do wyznaczenia optymalnych parametrów hydraulicznych dyszy zastosowano algorytm optymalizacji roju cząstek (PSO), a uzyskane wyniki zweryfikowano eksperymentalnie. Projekt ortogonalny obejmował ciśnienie w zakresie 200–300 kPa; algorytm PSO – na podstawie pełnego zbioru danych – wskazał optymalne ciśnienie 540 kPa. Zraszacz zainstalowano na wysokości 1,4 m nad poziomem gruntu w układzie kwadratowym. Optymalna kombinacja parametrów dla tego układu zapewniła wyższą równomierność rozkładu wody oraz kontrolowaną maksymalną energię kinetyczną w odniesieniu do średniej intensywności zraszania. Wyniki eksperymentu wykazały odpowiednio: 4,71 mm/h dla średniej intensywności zraszania, 83,28% dla współczynnika równomierności (CU) oraz 0,0078 $W \cdot m^{-2}$ dla maksymalnej energii

kinetycznej. W porównaniu z rozwiązaniem opartym na analizie zakresów, zoptymalizowana konfiguracja umożliwiła zmniejszenie średniej intensywności nawadniania przy jednoczesnej poprawie równomierności i charakterystyk energetycznych. Maksymalny błąd pomiędzy wynikami eksperymentalnymi a wynikami optymalizacji wyniósł 3,29%, co potwierdza wykonalność i wiarygodność zaproponowanego modelu optymalizacyjnego. Praca przedstawia praktyczne ramy optymalizacji, możliwe do zastosowania w projektowaniu i eksploatacji systemów nawadniania zraszaczowego.

Słowa kluczowe**:** BP-ANN, PSO, optymalizacja, wydajność hydrauliczna, zraszacz.