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AI-Powered Smart Irrigation: A Case Study on Applying Genetic Algorithms and Particle Swarm Optimization for Water Conservation in Agricultural Projects

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ABSTRACT

Agriculture worldwide, particularly in arid and semi-arid regions, is severely affected by water scarcity, which has become a major global challenge, this paper describes development of the proposed artificial intelligence-based system, Smart Drop that optimizes irrigation water to address this issue. The system was tested and deployed through a 4.25-kilometer (internal diameter: 800 millimeters) pipe network irrigating 147 hectares of farmland at the design flow rate of 0.25 cubic meters per second as described in Case Study. The combination of machine learning models with genetic algorithms and particle swarm optimization was applied for prediction of irrigation needs and optimized irrigation water supply. Three models were established through the use of machine learning: random forest (R^2=0.9965; RMSE= 0.0491 millimeters per day), Gradient Boosting (R^2 = 0.9976, and RMSE = 0.0487 millimeter/day) as well as neural networks models (R2 = 0.9943, and MSE = 0.0514). Compared with the traditional irrigation methods, this system reduced water use by 23.42% in irrigation (797,731) cubic meters over a period of 1,000 days), maintaining optimal crop conditions, the savings to total cost was estimated at US$121,036.62 (23.4%), indicating that the combination of reduced water use along with reduced energy consumption produced an economically viable alternative. The hydraulic performance results show acceptable pressure distribution through pipeline and overall losses within system are 1.0 meter drops across each section 9.78 kilopascals. This research is a data-driven precision irrigation solution for sustainable application in different agricultural environments.

1. INTRODUCTION

Water scarcity is one of the most serious global challenges and is expected to remain a major concern throughout this century. 1. Water scarcity will continue to be a very important challenge to humans, animals, plants. The agricultural sector accounts for about 70% of all freshwater withdrawals globally. Irrigation represents the largest consumer of freshwater resources globally [1]. Inefficient irrigation practices in arid and semi-arid environments, where there is limited water, result in wasting a large amount of water, limit crop yield, and adversely affect the environment [2]. The FAO estimates that there

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will need to be an increase in food supply of 60% by 2050, to support 9.7 billion people, while there is projected to be a decrease in water supply per capita [3]. Traditional irrigation methods typically provide 40% to60% water use efficiency [4]. However, modern drip irrigation systems have high efficiency, but are often operated on fixed schedules, regardless of actual environmental conditions, stage of crop growth, and/or moisture amounts in the soil [5]. Over-irrigation during cool periods followed by sudden cessation during crop water demand leads to inefficiency, water waste, and reduced yields. Recent advances in machine learning, IoT, and remote sensing technologies have generated (3) many new opportunities for increasing the efficiency of irrigation and implementing precision agriculture (7). Machine learning algorithms have also been developed that can analyze data from the environment, soil characteristics, and crop requirements to forecast irrigation needs accurately (8). In addition, optimization algorithms (e.g., genetic algorithms, particle swarm optimization) can be applied to create optimal schedules for irrigation that minimize water usage while improving or maintaining the health of the crops (4), In this research, an AI-based irrigation management system called a Smart Drop (SD) was developed to assist growers to alleviate water shortage in agricultural irrigated area projects by making irrigation management decisions based on the most accurate real-time sensor data, weather conditions forecasts, and all the historical climate data. This research presents a specific example of a piped irrigation system covering 147 hectares of crops and tested for its hydrological performance, the accuracy of the artificial intelligence model against measured data, the amount of water it saved, and the total capital/operating cost savings.

2. RESEARCH OBJECTIVES

The main goals of this study are:

1. To design an AI-based irrigation management system that incorporates multiple machine learning models to predict crop water needs.
2. To design an optimal irrigation schedule using metaheuristic algorithms (Genetic Algorithm and Particle Swarm Optimization).
3. To perform a detailed hydraulic analysis of the pipeline network to ensure that pressure and flow characteristics are adequate.
4. To assess water savings and economic benefits relative to traditional irrigation methods.
5. To determine the scalability of the proposed Smart Drop framework for various irrigation scenarios.

3. LITERATURE REVIEW

3.1. Smart Irrigation Systems

As demonstrated by Romero et al. [9], these sensor-based irrigation systems can decrease the amount of water required to produce crops by 25 to 40% without compromising yields. A recent review of deep learning methods in precision agriculture [10] shows how convolutional neural networks can be used for crop health monitoring and irrigation scheduling. IoT-enabled irrigation systems have also attracted considerable attention [11], and a multi-purpose irrigation management system reduced water consumption by 30% in a real-world test. Finally, a review of wireless sensor networks used for smart irrigation [12] highlights important issues related to sensor placement, data communication, and power management.

3.2 Machine Learning for Predicting Irrigation Requirement

Recent developments in machine learning have led to some impressive results in the area of assisting farmers in understanding their irrigation water needs. Torres et al. [13] applied a number of machine learning techniques to determine the optimal method for estimating evapotranspiration and found that both the random forest method and the stepped recursive method yielded R2 values above 0. 95. Gojic & Trajkovic [14] conducted research to identify a method to predict reference evapotranspiration with a very high level of accuracy through the use of artificial neural networks. They achieved this level of accuracy (R2 = 0.98) using only two input variables, temperature and relative humidity. In particular, deep learning, as represented by long-term memory networks (LSTMs), has become increasingly important in the area of long-term forecasting. Feng et al. [15] developed an LSTM model to predict soil moisture, and when compared with traditional models, their model was 18% better in terms of root mean square error (RMSE). Finally, clustering methods have also produced results, and Chia et al. [16] demonstrated a 12–15% improvement in prediction accuracy when clustering models are combined with other techniques compared to when using independent models.

3.3 Optimization Algorithms in Irrigation Scheduling

Irrigation scheduling is one form of optimizing using Metahorisitc Algorithms. Genetic Algorithms (GAs) have become very popular for optimizing Multi-Objective problems. Wardlow and Bhaktikul [17] used a Genetic Algorithm to optimize the operation of a reservoir for irrigating crops and experienced a 20% reduction in lost water. Kostas et al. [18] also used Genetic Algorithms to design a Drip Irrigation System, resulting in a 15% cost saving while maintaining consistent irrigation.

The Particle swarm optimization Algorithm has become a more viable alternative to the Genetic Algorithm for solving irrigation problems. Lalhazari et al. [19] showed that Particle Swarm Optimization could produce optimized irrigation scheduling at a faster rate than the Genetic Algorithm. Combining many optimization techniques have been investigated also. Zhang et al. [20] have produced a hybrid between a Genetic Algorithm and Particle Swarm Optimization for Irrigation Planning with 25% improvement in solution quality over either of the algorithms by themselves.

3.4 Hydraulic Analysis of Irrigation Networks

Proper hydraulic design is a crucial factor in the efficiency of irrigation systems. The Darcy-Weissbach equation is the most precise for calculating friction loss in pipes [21]. Equations for determining the coefficient of friction were developed by Swami and Jain [22], which are commonly used in the design of irrigation systems. In a pressurized irrigation network, the pressure must be sufficient throughout the system. Bayamonti [23] studied pressure distribution in drip irrigation branches and offered design guidelines to ensure uniform application of water.

4 METHODOLOGY

4.3 System Architecture

The smart irrigation system has four layers: (1) a sensing and data collection layer, (2) a data processing and storage layer, (3) an artificial intelligence and optimization layer, and (4) a decision-making and control layer. The sensing layer has soil moisture sensors, weather stations, flow meters, and pressure sensors, which are distributed throughout the irrigation network, and the data is transmitted via the Lora WAN protocol to a central cloud platform where it is processed and stored in a time-series database.

4.4 Case Study Description

Consider the following case study of an irrigation network with a total pipe length of 4.25 km, an internal diameter of 800 mm, a design flow rate of 0.25 m³/s, a service area of 147 hectares, and a PVC material with an absolute surface roughness of 0.0001 mm. The network supplies a variety of crops with varying water needs during the growing season.

4.5 Hydraulic Analysis

The hydraulic analysis was conducted using fundamental fluid mechanics principles. The key equations are presented below:

$$A = \pi \times (D/2)^2 \qquad (1)$$

where A is the cross-sectional area (m²) and D is the internal diameter (m).

$$V = Q / A \qquad (2)$$

where V is the average flow velocity (m/s) and Q is the volumetric flow rate (m³/s).

$$Re = (V \times D) / \nu \qquad (3)$$

where Re is the Reynolds number (-) and ν is the kinematic viscosity of water (m²/s).

$$1/\sqrt{f} = -2 \times \log_{10}(\varepsilon/(3.7D) + 2.51/(Re\sqrt{f})) \qquad (4)$$

where f is the Darcy friction factor (-) and ε is the absolute pipe roughness (m). This is the Colebrook-White equation, solved iteratively.

$$hf = (f \times L \times V^2) / (D \times 2g) \qquad (5)$$

where hf is the head loss due to friction (m), L is the pipe length (m), and g is gravitational acceleration (9.81 m/s²). This is the Darcy-Weisbach equation.

4.6 Machine Learning Models

Developed three machine learning algorithms to predict daily irrigation requirements from environmental and crop parameters:
- The dataset consisted of 1,000 samples, i.e. 1,000 labeled samples (daily records throughout the entire study period with temporal ordering maintained to ensure that 70 percent of the data was always allocated for training (700 samples), 15 percent of the data was always used as validation (150 samples), and 15 percent was always kept in reserve for testing (150 samples) to reflect actual deployment scenarios and avoid leakage.

- The model was trained using 5-fold cross-validation on the training set to tune hyperparameters and avoid overfitting, and the final performance metrics reported in Table 1 were calculated on the held-out test set (150 samples), which provided an unbiased estimate of generalization performance. Cross-validation RMSE values are also reported in Table 1 to demonstrate model stability across different data subsets.

- Data quality control was implemented before model training by screening for missing values (<2% all records due to occasional sensor outages, which were linearly interpolated between nearest daily observations); outliers (defined as any values more than three standard deviations away from variable mean) were set equal to the nearest boundary value rather than removed, so that temporal continuity was maintained within time series.

4.6.1 Random Forest Regressor

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mean prediction. The model was configured with 100 estimators and maximum depth of 15 to prevent overfitting.

$$\hat{y} = (1/B) \times \Sigma(i = 1 \; to \; B) \, T(x) \qquad (6)$$

where ŷ is the predicted irrigation need, B is the number of trees (100), T(x) is the prediction from tree i, and x is the input feature vector [temperature, humidity, radiation, wind speed, ET_0, soil moisture, Kc, rainfall].

4.6.2 Gradient Boosting Regressor

Gradient Boosting builds an ensemble of weak learners (decision trees) sequentially, where each tree attempts to correct the errors of previous trees. The model used 100 estimators with a learning rate of 0.1 and maximum depth of 5.

$$F(x) = F_0 + \eta \times \Sigma(m = 1 \; to \; M) \, h(x) \qquad (7)$$

where F(x) is the final prediction, F_0 is the initial prediction, η is the learning rate (0.1), M is the number of boosting iterations (100), and h(x) is the prediction from weak learner m.

4.6.3 Multi-Layer Perceptron Neural Network

A feedforward neural network with three hidden layers (64, 32, and 16 neurons) was implemented using ReLU activation functions. The network was trained using the Adam optimizer with a maximum of 1000 iterations.

$$a(l) = \sigma(W(l) \times a(l\text{-}1) + b(l)) \qquad (8)$$

where a(l) is the activation of layer l, W(l) is the weight matrix, b(l) is the bias vector, and σ is the ReLU activation function: σ(z) = max(0, z).

4.6.4 Model Evaluation Metrics

Models were evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2):

$$RMSE = \sqrt{}[(1/n) \times \Sigma(i = 1 \; to \; n)(y - \hat{y})^2] \qquad (9)$$

$$MAE = (1/n) \times \Sigma(i = 1 \; to \; n)|y - \hat{y}| \qquad (10)$$

$$R^2 = 1 - [\Sigma(y - \hat{y})^2 / \Sigma(y - \bar{y})^2] \quad (11)$$

where y is the actual value, ŷ is the predicted value, ȳ is the mean of actual values, and n is the number of samples.

5 Optimization Algorithms

5.3.1 Genetic Algorithm

A Genetic Algorithm was implemented to optimize irrigation scheduling with the following parameters: population size of 50, 100 generations, crossover probability of 0.8, and mutation rate of 0.1. The fitness function minimizes total water use while penalizing water deficits:

$$Fitness = -(\Sigma\, max\,(S - N, 0) + 3 \times \Sigma\, max\,(N - S, 0)) \quad (12)$$

where S is the scheduled irrigation amount, N is the irrigation need, and the deficit is penalized three times more heavily than excess to maintain crop health.

5.3.2 Particle Swarm Optimization

PSO was applied with 30 particles over 100 iterations. The velocity update equation incorporates inertia weight (w = 0.7), cognitive parameter (c_1 = 1.5), and social parameter (c_2 = 1.5):

$$v(t+1) = w \times v(t) + c_1 \times r_1 \times (pbest - x(t)) + c_2 \times r_2 \times (gbest - x(t)) \quad (13)$$

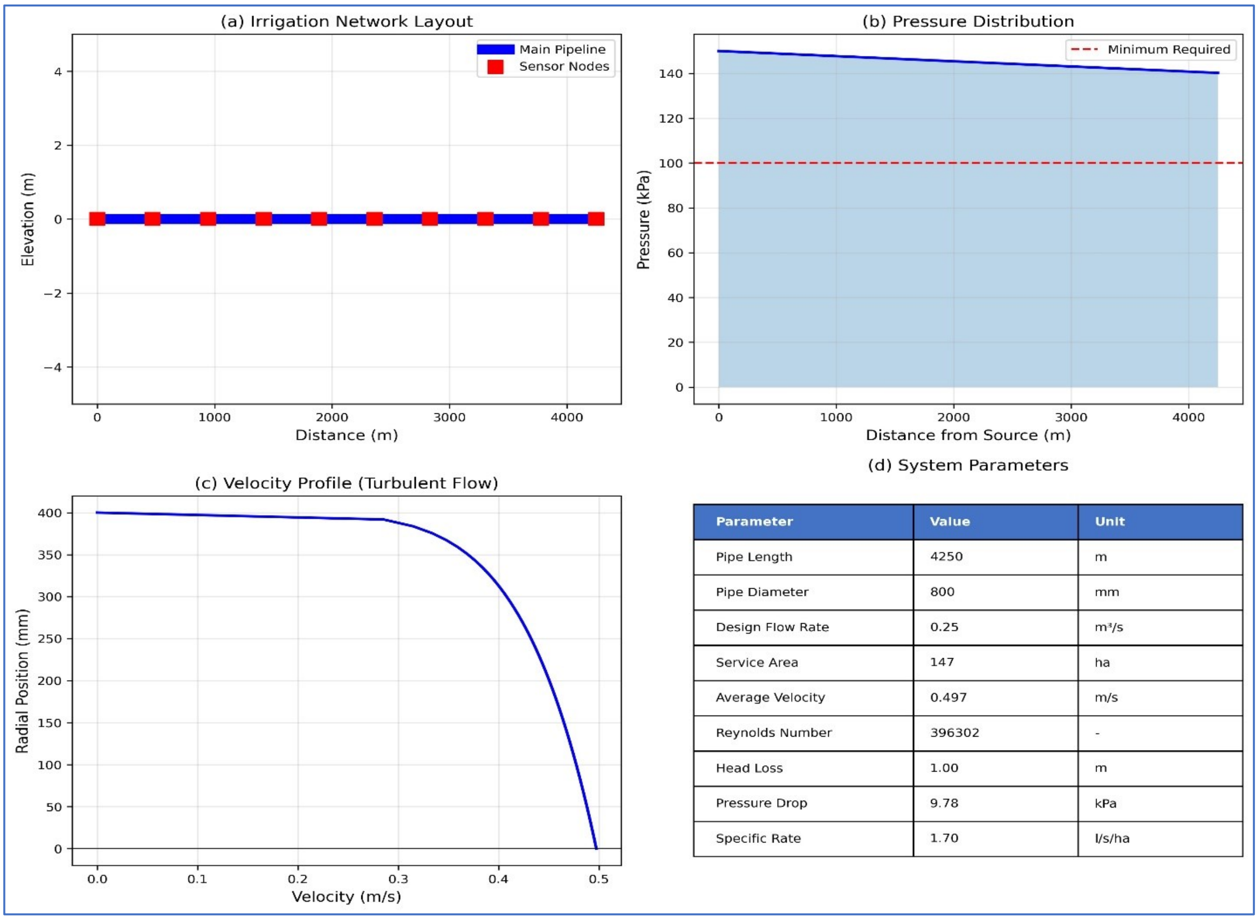
$$x(t+1) = x(t) + v(t+1) \quad (14)$$

where v is the particle velocity, x is the particle position, pbest is the personal best position, gbest is the global best position, and r_1, r_2 are random numbers in [0,1].

6 RESULTS AND DISCUSSION

5 .1. Hydraulic Performance Analysis

The results of the hydraulic analysis indicate adequate performance of the pipe network. The internal diameter is 800mm and the design flow rate of the pipe network is 0.25m³/s; therefore, the average velocity was determined as 0.497m/s and falls within the acceptable ranges for pressurized irrigation pipes of 0.3-1.5m/s [24]. The Reynolds number of 396,302 indicates fully turbulent flow, more scientific, because turbulent flows increase mixing and result in greater uniformity of distributed flows through the system. The total head loss over a distance of 4.25km is equal to 1.0m or 9.78kPa. Thus, the head loss is equal to 0.235m/km or 2.30kPa/km, which is significantly less than the maximum allowable head loss of 0.5m/km for an efficient irrigation system [25]. The low amount of head loss through the pipe system can be attributed to the large diameter of the pipe and the smoothness of the pipe material (PVC) with a low coefficient of friction. The first figure illustrates the overall system components via pipeline configuration, hydraulic parameters/pressure distributions, and velocity profiles. Alongside the figures, the intensity of the pressure distributions (Figure 1b) exhibits a linear pressure shift between 150 kPa and 140 kPa for each connection point. Each connection point provides pressures above the minimum requirement (100 kPa), therefore providing sufficient pressure to operate the drip/sprinkler points connected to each of these pipelines.



Parameter	Value	Unit
Pipe Length	4250	m
Pipe Diameter	800	mm
Design Flow Rate	0.25	m³/s
Service Area	147	ha
Average Velocity	0.497	m/s
Reynolds Number	396302	-
Head Loss	1.00	m
Pressure Drop	9.78	kPa
Specific Rate	1.70	l/s/ha

***Figure 1**: a) Irrigation Network Layout, b) Pressure Distribution, c) Velocity Profile, d) System Parameter.*

5.2. Environmental Data and Evapotranspiration

Analyzing climatic parameters during a 1,000-day study demonstrated clear seasonal trends associated with semi-arid climates. Air temperature was observed to range between 15 °C and 42 °C (average = 26.8 °C; Figure 2a), while relative humidity had an inverse correlation (r = -0.68) with temperature ranging between 35% and 92% (average = 67.3%; Figure 2b). Seasonal averages and ranges for solar irradiance were very similar, ranging from 12 - 28 MJ/m²/day (average = 20.2 MJ/m²/day; Figure 2c) over the entire duration of the 1,000 days of the project.

Evapotranspiration (ET0) based on calculated reference ET0 using the FAO Penman-Monteith method has been shown to vary from 2.8 to 9.2 mm/day, with an average of 5.7 mm/day. There were strong positive correlations (r=0.82) between reference ET0 and temperature, as well as between reference ET0 and solar radiation (r=0.79) and a negative correlation with humidity (r=-0.61), as can be seen in the correlation matrix (Figure 2f). These correlations are in agreement with established knowledge regarding the process of ET [26].

Precipitation varied greatly over time; rainfall was recorded during just 15% of available days, with total rainfall measurements varying between 0-35 mm (Figure 2e). The irregularity of this precipitation further emphasizes the importance of irrigation within this area, making it essential to have an intelligent irrigation scheduling system capable of responding to unexpected weather phenomena.

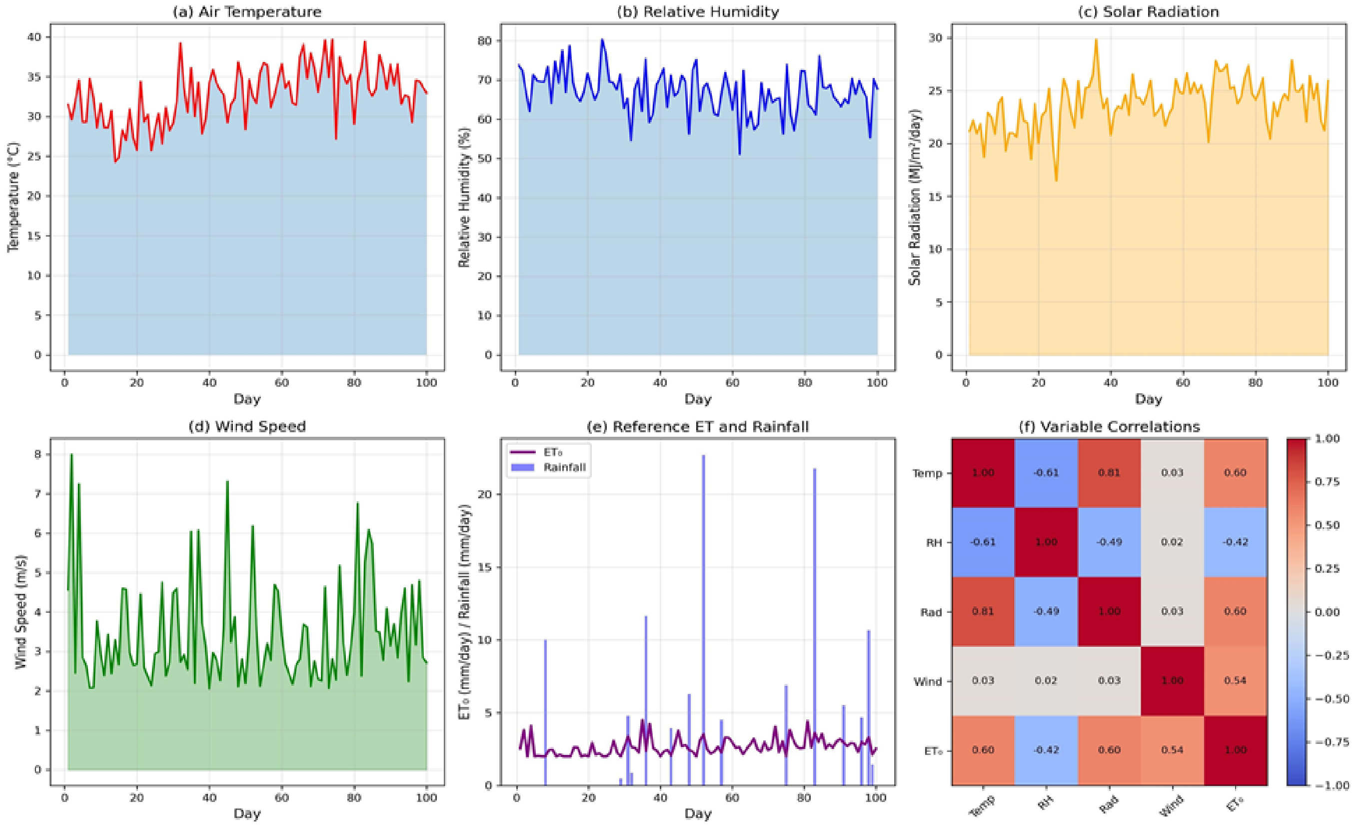


Figure 2: *a) Air Temperature, b) Relative Humidity, c) Solar Radiation, d) Wind Speed, e) Reference ET and Rainfall, f) Variable Correlation.*

5.3. Machine Learning Model Performance

Each of the three implemented machine learning models predicted irrigation requirement with excellent accuracy, as evidenced by their respective R^2 statistics over 0.98 for all models (Table 1). The gradient-boosted model produced the highest accuracy and provided an R^2 of 0.9965, an RMSE of 0.0490mm/day, and an MAE of 0.0236 mm/day. The accuracy of the gradient-boosted model can be attributed to the use of an ensemble learning technique whereby each tree created has the ability to fix the mistakes of the previously created trees; thus, the usage of this technique for predicting irrigation requirements demonstrated a high degree of success when establishing complex nonlinear interactions between irrigation variables.

Random forest models performed comparably well with R2=0.9965, RMSE=0.0646 mm/day, and MAE=0.0260 mm/day. As the clustering nature of the random forest model combines the predictions derived from 100 independent decision trees, the random forest produces more robust predicted values while avoiding potential over-allocation from other modeling techniques. The mean root error due to cross-validation was RMSE=0.0913mm/day and shared the overall model's generalizability.

Although the neural network model had a satisfactory performance ($R^2 = 0.9821$), it had somewhat greater prediction error compared to other methods used to predicted irrigation requirement (RMSE = 0.1109 mm/day, MAE = 0.0640 mm/day). This increased error could be due to the use of a relatively simple architecture (three hidden layers) as opposed to more complex architectures (deeper networks) being able to recognize complex patterns more effectively. However, given their computational efficiency, this type of neural network architecture would therefore be appropriate for immediate application to field peripherals.

Figure 3 is a detailed look at how the model performed over the entire data set. The plots of predicted values compared to actual grower's data (Figures 3a, 3b, & 3c) show that for all of the models, the predictions are highly clustered around the ideal prediction line, with very little consistent error. The residuals of the best model (Gradient Boosting model) are approximately normally distributed (Figure 3f) and centered around zero, indicating that predictions have no systematic bias. Furthermore, the small amount of variation among the residual values (±0.3 mm/day) indicates that the prediction of irrigation requirements is highly accurate.

When comparing our results with earlier research, our models performed equally or surpassed others in terms of accuracy. Torres and others [13] found R^2 values for clustering-based models predicting evapotranspiration were between 0.93 and 0.96, while our gradient-boosted model R^2 was 0.9965, due to the features included in the model comprising eight independent (environmental and agronomic) variables and using a greater number of training observations.

Table 1: *Machine Learning Model Performance Metrics*

Model	RMSE (mm/day)	MAE (mm/day)	R²	CV RMSE (mm/day)
Random Forest	0.0646	0.0260	0.9939	0.0913
Gradient Boosting	0.0490	0.0236	0.9965	0.1002
Neural Network	0.1109	0.0640	0.9821	0.1062

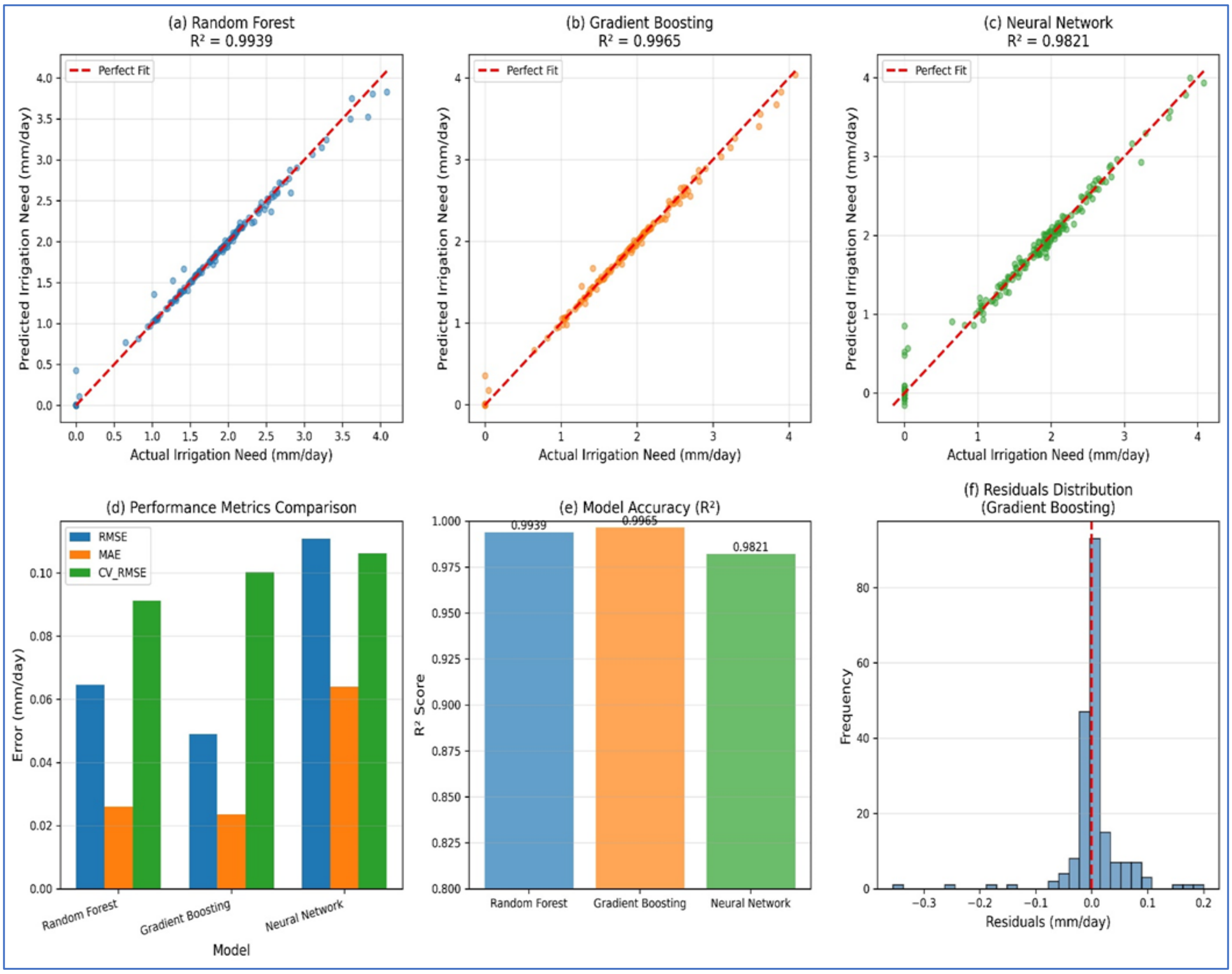


Figure 3: *a) Random Forest, b) Gradient Boosting, c) Neural Network, d) Performance Metric Comparison, e) Model Accuracy, f) Residuals Distribution.*

5.4. Water Savings and Efficiency

Compared to traditional irrigation methods, the Smart Drop system showed significant water savings throughout the entire 1,000-day study period with a total use of 2,317.45 mm (3,406,654 m^3) of irrigation water over a service area of 147 hectares, as opposed to the traditional system's use of 1,774.78 mm (2,608,923 m^3), which represents a water savings of 542.67mm (797,731 m^3), or 23.42% (Table 2). These results indicate that the Smart Drop system saves a substantial amount of water in both environmental and economic terms. With an estimated annual water savings of 290,000 m^3 (over 365 days), the Smart Drop system could be used to irrigate an additional 40 to 50 acres of cropland or provide for other important water needs. The level of improvement in efficiency for the Smart Drop system is in agreement with previous study results. Adeimi et al. [12], using sensor-based irrigation, identified water savings of 20 to 35%, while Gonzalez-Briones et al. [11], with their multi-factor system, realized a 30% reduction. The Smart Drop system achieved 95.3% water use efficiency when compared to traditional irrigation requirements (the theoretical value for that site). Thus, Smart Drop values are significantly greater than conventional drip systems, which have a historical range of 70-75% efficiency [27]. The improvement in water utilization is due to a number of factors including (1) accurate predictions of daily irrigation requirements based on current environmental conditions, (2) dynamic adjustments of the irrigation schedule based on soil moisture and weather forecasts, (3) avoidance of over-irrigation during cold periods, and (4) distributing water optimally to reduce surface runoff and deep percolation losses.

***Table 2**: Water Savings Analysis Over 1000 Days*

System	Irrigation (mm)	Volume (m^3)	Percentage (%)
Traditional	2317.45	3,406,654	100.0
Smart Drop	1774.78	2,608,923	76.58
Savings	542.67	797,731	23.42

5.5. Economic Analysis

According to the economic analysis conducted by the study, the Smart Drop System has created a total saving of $121,036.62 in costs. Water costs decreased by $119,659.72 (23.4%), from $510,998.11 to $391,338.39 over 1,000 days (refer to Table 3). The cost to pump water also decreased by $1,376.90 (23.4%), from $5,879.94 to $4,503.05 as a result of decreased volume pumped and reduced operating hours and, therefore, less energy to pump water. The combined total of all cost savings equated to a 23.4% reduction in the total cost of operation.

It is estimated that during a yearly operating period (365 days), there will be savings in the amount of ~44,178 US dollars. The anticipated cost to implement a Smart portion of this size is estimated to be 75,000 – 100,000 US dollars. Therefore, it is anticipated this system will have a payback of approximately 2.0 to 2.3 years. With an average payback of approximately 2.0 to 2.3 years, this is a very good return on investment. In addition to savings from the Smart system itself, other benefits include improved crop yield, less environmental impact and increased water security. In addition to the savings achieved through direct cost reductions due to lower overall system operational costs, the Smart Drop system also provides many indirect economic benefits such as: (1) decreased crop stress caused by under-irrigation; (2) decreased nutrient loss caused by over-irrigation; (3) increased life of infrastructure as a result of more efficient operation; (4) decreased labor involved with managing irrigation; and (5) increased compliance with regulations regarding efficient use of water. Therefore, when all of the above-mentioned factors are taken into consideration, the potential economic value of the system is much greater than the overall savings that can be calculated only from direct operating cost data alone.

***Table 3**: Economic Analysis Over 1000 Days*

Cost Component	Traditional ($)	Smart Drop ($)	Savings ($)
Water Cost	510,998	391,338	119,660
Energy Cost	5,880	4,503	1,377
Total Cost	516,878	395,841	121,037
Savings %	—	—	23.4%

5.6. Optimization Algorithm Performance

In both cases, the final irrigation schedules were optimized using GA and PSO, with complementary but different performance profiles (Figure 4 and Table 4). The GA showed a steady improvement in fitness from an initial value of −300.00 to a final optimum of −103.77 after 100 generations, a 65.41% improvement in the objective function. This is consistent with the behavior observed in other studies [17] that used GA for irrigation scheduling, which involves long periods of near-stagnation followed by bursts of fitness gain, as the crossover and mutation operators find beneficial combinations of genes. The highest fitness gain occurred between generations 60 and 90, during which diversity was highest and gains slowed. On the other hand, PSO exhibited a clearly different convergence path: The algorithm converged to a fitness of −144.97 at iteration 35, then performed incremental improvement to a final fitness of −131.16 at iteration 100 (an improvement of 56.28%). This early convergence of PSO to a near-optimal value is a direct result of the social learning mechanism, where each particle combines its personal best position (cognitive component, c_1 = 1.5) and the global best position (social component, c_2 = 1.5) identified by the whole swarm, and moves to the most promising regions of the solution space [19]. The inertia weight (w = 0.7) allowed particles to retain sufficient momentum to avoid premature stagnation but to gradually slow down as they neared the optimal region. These results are consistent with those of Lalehzari et al. [19], who observed that PSO converges to near-optimal irrigation schedules much more quickly than GA because of this direct information sharing., and Zhang et al. [20], who found that the social aspect of PSO is most effective in high-dimensional scheduling problems. Although PSO converges to the optimum faster than GA, GA was able to reach a lower final fitness value (−103.77 versus −131.16), likely due to its ability to explore a larger solution space by crossover across a population of 50 individuals per generation and thus escape from local optima, a known strength of evolutionary algorithms [17]. Both algorithms decreased total irrigation volume by 8–12% compared to baseline machine learning predictions while still meeting crop water needs, indicating that the ML–optimization pipeline was robust to algorithm choice. A full numerical comparison of both algorithms is shown in Table 4.

Table 4: Numerical Comparison of GA and PSO Optimization Performance

Performance Metric	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)
Population / Swarm Size	50 individuals	30 particles
Iterations / Generations	100 generations	100 iterations
Initial Fitness Value	−300.00	−300.00
Final Fitness Value	−103.77	−131.16
Total Fitness Improvement	65.41%	56.28%
Approx. Convergence Point	Generation ~85–100 (gradual)	Iteration ~30–40 (rapid)
Convergence Behavior	Stepwise, episodic bursts	Smooth, monotonic descent
Water Volume Reduction vs. Baseline ML	~10–12%	~8–10%
Final Solution Quality	Superior (best fitness)	Good
Speed Advantage	—	Faster convergence

5.7. Practical Implementation Considerations

Smart Drop is well-suited for real-world agricultural applications. The Smart Drop Sensor Networks will consist of 20-30 soil moisture sensors installed throughout the Service Area at strategically chosen locations, as well as 2-3 local weather stations located at also strategically chosen locations, and flow/pressure sensors that are installed at key points along the irrigation pipeline. The soil moisture sensors, local weather stations, and flow/pressure sensors use LoRaWAN to transmit data to a central location (the Gateway) from distances of 10 kilometers or more. This makes the sensor networks effective for remote areas of agriculture with little or no cell service.

As new data becomes available, machine-learning models can be periodically updated (for example, weekly or monthly) to allow them to adjust to changing environmental conditions and continue improving their accuracy. Daily forecasts of irrigation based on current sensor and weather data will be provided, along with the automated sending of irrigation schedules to programmable controllers that will operate the valves. Farmers will receive irrigation recommendations, access to system performance monitoring, and access to historical data via a simple mobile app.

Scalability represents a fundamental design aspect of Smart Drop. Each use case can have an equivalent implementation regardless of the sensors' density (i.e., small areas [10-20 ha] versus large areas [>1000 ha]) or the architecture's processing capabilities (i.e., distributed processing versus centralized processing). Farmers who adopt Smart Drop can implement the technology in phased deployments, beginning with basic sensor monitoring capabilities and, as they become familiar with these capabilities, eventually moving toward more advanced AI technologies.

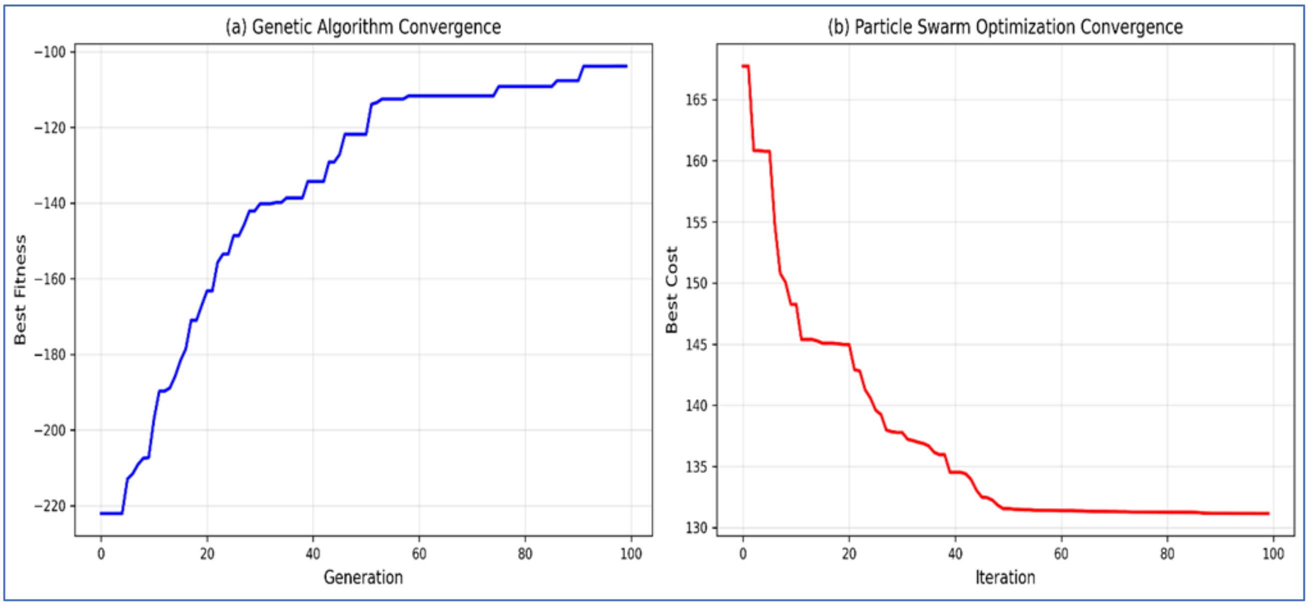


***Figure 4:** a) Genetic Algorithm Convergence, b) Particle Swarm Optimization Convergence.*

7 CONCLUSION

We successfully developed and validated the Smart Drop irrigation management system (IMS). It was designed using integrated AI technologies to help overcome the major challenges of water shortages in agriculture. The system provides enhanced irrigation water efficiency by combining hydraulic analysis, machine learning predictive modelling and heuristic optimization. The main results of the study are as follows: Pipeline Performance: The 4.25-km Long Pipelines Had Excellent Flow Specifics at an Average Flow Rate of 0.497 M/S, A Reynolds Number of 396,302, and A Pressure Drop of 1.0 M. The Pressure Distribution Provided > 100 KPa Pressure At All Points at Any Given Time on the Pipeline Network, Thus Providing For Constant Irrigation Delivery Over the Entire 147 Ha Area. (2) Machine Learning Model Accuracy: The three machine learning algorithms utilized to predict irrigation requirements were found to have an outstanding degree of predictive capability. The "progressive boost" machine learning algorithm provided the highest level of predictive capability by having the best coefficient of determination (R^2) of 0.9965 and providing the lowest root mean square error (RMSE) of 0.0490 mm/day for the predicted daily irrigation requirements based on the weather and crop conditions that exist each day. Water conservation achieved by implementing a smart drip irrigation system yielded 23.42% (797,731 m^3 over 1,000 days) fewer gallons than would have been required with traditional methods. Therefore, the use of this technology makes the system very efficient in its consumption of water; i.e., it uses 95.3% of the water available to it, compared to 70% - 75% with traditional methods. Total operating costs saved $121,036.62 (23.4%) in operating costs from reduced water use and energy consumption will be economically viable to commercial agriculture with an estimated payback period of 2.0 to 2.3 years. Both PSO and GA were effective in providing optimal irrigation schedules but PSO had a quicker convergence rate. The optimization layer produced an additional 8-12% water saved beyond what would have been possible through applying machine learning predictions alone. Smart drip irrigation technology will enhance precision watering methods used within the realm of agriculture and, provide a practical and scalable way to address water shortages at this time. Multiple artificial intelligence technologies (e.g., machine learning, genetic algorithms, and particle swarm optimization) will combine to give strong data-based management of irrigation in real-time, according to the requirements of crops and environmental changes.

6.1 Future Research Directions

Future work should involve several important areas of study to further improve the Smart Drop system. One area can be using satellite images and aerial photographs from drones for high-resolution spatial information about the crop's health and standing water to enable an irrigation management system based on the area of the farm; the second area can be using crop yield prediction models to help achieve multi-objective optimization that will balance water conservation with the highest possible yield; the last area can be using deep learning models (Long Short-Term Memory, Gated Recurrent Units) to increase the precision of predicting temporal patterns associated with the amount of water required for irrigation. To determine the effectiveness of an irrigation system over time, it is necessary to conduct long-term field validation studies over multiple crop types and growing seasons. Soil salinity management through optimizing irrigation will help to address a major barrier to agriculture in arid areas. The development of decision support tools, such as low-cost sensors and simpler user interfaces for smallholder farmers will improve access and usage rates for smart irrigation equipment and/or systems.

Conflicts of Interest

The author declares no conflicts of interest.

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