

Design of Algorithm-Driven Household Intelligent Irrigation System Model: Case Study on Tomato and Spinach

Tianhui Zhuang

*Dalton Academy, The Affiliated High School of Peking University, Beijing, China
zhuangtianhui2027@i.pkuschool.edu.cn*

Abstract. Traditional irrigation always relies on fixed schedule or manual watering, which easily cause water waste, overwatering and underwatering problems. These issues adversely affect crop growth and sustainable water utilization. Existing intelligent irrigation systems often have low pertinence on specific plants, lacks research on small-scale irrigation, relies on fixed thresholds and are costly. Without accessible adaptive technology, growers will face higher water bills, and the plants might be damaged by improper irrigation strategies. This study designs a low-cost household intelligent irrigation system model. The study first finds basic irrigation amount by using ΔH method, and then use Artificial Intelligence (AI) image recognition to detect growth condition, applies Application Programming Interface (API) integration and Proportional-Integral-Derivative (PID) dynamic adjustment to correct irrigation amount, applies scale ratio calculation to change irrigation amount and uses Recursive Least Squares (RLS) algorithm to adaptively adjust control parameters. Simulation results indicate that the model achieves an obvious water-saving rate, which verifies the feasibility of integrating electronics modules with algorithmic control for water saving and plant growth regulation.

Keywords: agricultural engineering, household intelligent irrigation system, AI image recognition, PID controlling algorithm, RLS parameter estimation

1. Introduction

With population growth and ongoing climate change, efficient and water-saving irrigation management has become a key demand for sustainable agricultural development. Traditional irrigation methods still face many practical limitations in actual use. Most conventional irrigation strategies are unreasonable in design, resulting in low water use efficiency and potential environmental degradation [1, 2]. In small-scale planting scenarios, including family cultivation and miniature greenhouses, growers usually arrange irrigation according to personal experience rather than objective data. Empirical watering often leads to over-irrigation or insufficient water supply, which affects crop growth and fails to meet the requirements of sustainable agricultural development [3]. Existing studies have explored the correlation between crop growth stages and water demand, and have attempted to adjust irrigation volume based on soil moisture and temperature conditions. Basic intelligent algorithms and sensing technologies have also been preliminarily applied in irrigation practice [4-6].

Current research generally focuses on improving irrigation water use efficiency (IWUE). Nevertheless, most existing studies concentrate on large-scale farmland irrigation, while paying insufficient attention to household intelligent irrigation and crop-specific irrigation strategies [7]. In addition, most existing systems cannot effectively identify abnormal crop growth states or cope with extreme weather disturbances. At present, many irrigation devices are unable to dynamically adjust water supply according to real-time crop growth performance and changing environmental conditions. To address these research gaps, it is necessary to develop a small-scale irrigation system suitable for specific crops with dynamic adjustment capability.

In practical application, this study constructs an algorithm-based household intelligent irrigation model to solve common irrigation problems in small-scale agricultural planting. The system can remind users of abnormal crop growth and dynamically adjust irrigation volume in response to real-time environmental changes and upcoming extreme weather. This design reduces the reliance on personal planting experience, allowing small-scale growers to implement precise irrigation through systematic intelligent control. Scientific irrigation not only maintains healthy crop growth but also improves water-saving performance. Academically, this study adopts potted plant experiments to determine the basic irrigation volume by analyzing soil moisture changes before and within 24 hours after watering. The system integrates multiple technical modules: AI image recognition for growth stage classification, weather API data for abnormal condition monitoring, PID algorithm for dynamic irrigation adjustment, and scale ratio and RLS optimization for environmental adaptation. The experimental results verify the feasibility and effectiveness of applying these algorithms to low-cost household irrigation scenarios.

This study targets several common defects of traditional and existing intelligent irrigation systems, including poor crop pertinence, insufficient research on household irrigation, fixed irrigation thresholds and high application costs. Taking tomatoes and spinach as experimental crops, this paper develops a complete household intelligent irrigation system model. The model can calculate basic irrigation volume, monitor abnormal crop growth, and realize real-time dynamic irrigation adjustment according to external environmental changes. This research provides practical references for the development of energy-saving and eco-friendly precision agriculture, and verifies the application potential of image recognition, weather API, PID control, scale ratio calculation and RLS algorithms in low-cost household intelligent irrigation systems.

2. Related work

2.1. Traditional irrigation systems and limitations

At present, most agricultural regions in China still adopt traditional irrigation methods, which suffer from severe water waste, low water utilization efficiency, empirical operation and insufficient dynamic regulation.

Firstly, crop water demand is determined by crop types, soil conditions and meteorological factors, all of which change dynamically during the growth cycle [1]. However, traditional irrigation approaches fail to adjust irrigation schedules according to real-time temperature, air humidity and soil moisture variations.

Secondly, China's agricultural water utilization efficiency remains relatively low, demonstrated that the irrigation utilization coefficient of high-income countries reaches approximately 0.75, while that of China is only 0.58 [2]. Nearly 40% of irrigation water is wasted due to outdated techniques and improper field management [2]. Thus, efficiency improvement requires an intelligent system that adapts water supply to crop types, growth stages and real-time environmental conditions.

Thirdly, field-level irrigation management is generally inadequate. The U.S. Environmental Protection Agency (EPA) indicated that the most common management method in traditional irrigation systems relies on clock-timer controllers that the users previously set [3]. Most growers determine irrigation volume purely by experience without standardized and scientific management guideline. Overall, conventional irrigation systems lack practical, data-driven management modes, especially for small-scale individual farmers.

2.2. Existing irrigation systems and limitations

With the rapid development of agricultural intelligence, various intelligent irrigation systems have been proposed to address the drawbacks of traditional irrigation. This section reviews representative studies and summarizes their technical advantages and application effects.

Qu developed a water-saving irrigation system based on ZigBee and MESH networks for real-time soil humidity and fertility monitoring. The system provides visualized sensor data to support growers in independently setting irrigation duration and water volume. It adaptively adjusts irrigation strategies according to corn growth stages and weather conditions to guarantee stable crop growth. Practical verification shows that the system reduces irrigation water consumption by 30% and fertilizer usage by 25%, while increasing crop yield by 20% and economic benefits by 31% [8].

Cai et al. applied a CNN model to automatically identify water level images and calculate net irrigation water volume. By fitting the water level–flow curve, the team obtained an effective irrigation utilization coefficient of 0.5014 based on practical water consumption statistics [9]. This method significantly improves the precision of irrigation volume measurement and provides reliable support for refined agricultural water management.

Wang integrated IoT sensing and human–computer interaction techniques to build a real-time irrigation monitoring system. The system collects multi-dimensional environmental data and constructs an evaporation prediction model based on LSTM and Keras frameworks. It uploads field growth and soil data to a remote platform, which triggers alarms and automatic valve activation when soil moisture exceeds 22% [5].

Focusing on greenhouse tomato cultivation, Wu designed an intelligent irrigation system combining PLC control and IoT technology. The cloud platform adjusts irrigation schemes according to real-time crop growth status and realizes intelligent irrigation optimization. It also displays crop growth information and optimizes control strategies based on user feedback [6].

In general, current intelligent irrigation systems integrate IoT sensing, deep learning prediction and intelligent control technologies, effectively improving irrigation refinement, reducing water waste and enhancing planting economic benefits.

2.3. Gaps and the research focus

Despite the progress of intelligent irrigation technologies, practical applications still have obvious limitations. This section summarizes key research gaps and clarifies the core focus of the present study.

Firstly, most existing systems adopt universal designs without targeted optimization for specific crop growth characteristics. Current irrigation strategies mainly depend on general indicators such as temperature and soil moisture, but fail to quantify the dynamic correlation between environmental changes and crop water demand across different growth stages. Abdelmoneim et al. suggested that future irrigation research should prioritize modular systems that integrate crop-specific water demand and environmental variables [7].

Secondly, insufficient attention has been paid to household small-scale irrigation. According to Sowby and Lunstad's study, residential irrigation accounts for 30%–50% of domestic water use in most regions, and can even reach 90% in some areas. Nevertheless, household irrigation is generally inefficient and has become a critical issue in modern water resource management [10]. Existing intelligent irrigation research mainly targets large-scale farmlands, while household-oriented irrigation solutions remain insufficient.

Thirdly, most systems lack flexible dynamic adjustment ability. Conventional intelligent irrigation platforms rely on fixed single thresholds and single-parameter control. As illustrated by Lin et al. [11], typical systems such as AgriTalk trigger irrigation merely based on static soil moisture thresholds. Such rigid mechanisms cannot achieve adaptive irrigation adjustment by comprehensively coupling multiple environmental factors.

Finally, mainstream intelligent irrigation solutions depend on high-cost hardware, limiting their popularization. Abdelmoneim et al. pointed out that future irrigation technology tends to be low-power, scalable and cost-effective. Most existing systems, represented by the framework proposed by Zia et al., are designed for large-scale farms with high hardware costs, making them difficult to deploy in small-scale household planting scenarios [1].

In summary, current studies suffer from poor crop pertinence, insufficient household irrigation research, rigid threshold-based control and high application costs. This study addresses these limitations by determining basic irrigation parameters via pot experiments, monitoring crop growth status through AI image recognition, and dynamically correcting irrigation volume based on real-time environmental variations.

2.4. Summary

Traditional irrigation modes are restricted by backward techniques, low water utilization efficiency and unscientific management mechanisms [1-3]. Although recent studies have integrated intelligent technologies to improve irrigation performance, existing systems still have prominent defects, including weak crop pertinence, insufficient support for small-scale irrigation, inadequate dynamic adjustment and high deployment costs.

To fill these research gaps, this study develops a low-cost intelligent irrigation controller system. It determines baseline irrigation volume through pot experiments, identifies crop growth stages and abnormal growth via AI image recognition, and realizes dynamic irrigation adjustment by integrating weather API, PID control, scale ratio calculation and RLS optimization algorithms.

3. Methodology

This chapter introduces the experimental and analytical methods for determining and dynamically adjusting the irrigation amount for tomato and spinach after getting ΔH verses I plot and plants images from pot experiment. The proposed methods include several phases: selecting basic irrigation amount using ΔH method, detecting growth conditions by AI image recognition technology, weather and PI based correction algorithms to adjust irrigation in real time, adapting updated of parameters by using scale ratio calculation and RLS-based adaptation and transforming irrigation amount into irrigation duration by Torricelli's principle. Finally, a water saving rate calculation is applied to evaluate the irrigation performance. The following sections detail each component of the methodology.

3.1. Selection of basic irrigation amount

According to Wang et al.'s study, soil moisture at 70%~89% field capacity optimizes irrigation amount. The increase of irrigation amount leads to unnecessary water consumption, and the decrease makes the soil dry [12].

The ΔH value serves as an indicator of the water balance relationship $I - E - A$, where I is the irrigation amount, E represents evaporated water, A represents water absorbed by plants. According to this water balance model, data that have following ΔH values should be eliminated:

- If $\Delta H < 0$, either irrigation was insufficient ($I < E + A$) or excessive ($I > E + A$).
- If $\Delta H \approx 0$, the applied water was nearly fully consumed by evaporation and plant absorbance ($I \approx E + A$), indicating insufficient buffer to against sudden environmental changes.

If ΔH decreases over consecutive irrigation levels, all data within that interval should be eliminated, as such nonmonotonic behavior reveals an unstable soil moisture condition, which are unsuitable for reliable irrigation management.

Second, the middle point of I in the remaining steadily increasing ΔH interval to be the I_{base} in each growth stages are chosen. If there is not steadily increasing ΔH interval, irrigation amount range should be reset, and the measurement should be done again.

3.2. AI-based recognition of plant growth conditions

This study adopts the Roboflow platform for lightweight plant growth image classification [13]. The platform integrates image annotation, preprocessing, model training and evaluation functions, which enables rapid construction of plant visual recognition models. For each growth stage of tomatoes and spinach, 150 valid plant morphological images are collected.

All images are manually annotated using the Segment Anything Model 3 (SAM3) Smart Select tool. The classification labels cover five normal growth stages, including tomato seedling (TS), tomato flowering (TF), tomato fruiting (TFR), spinach seedling (SS), and spinach rapid growth (SR). Two typical abnormal growth states are additionally labeled, namely spinach heading and tomato leaf withering. The entire dataset is automatically and randomly split into 70% for training, 20% for validation, and 10% for testing. Model training loss and classification accuracy curves are generated after training convergence.

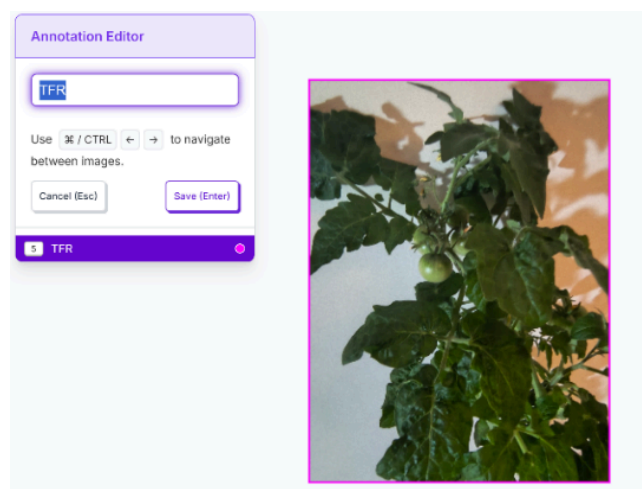


Figure 1. Example of annotation for a tomato's fruiting stage image (photo credit: original)

Figure 1 shows an annotated example of a tomato fruiting stage sample. The SAM3 model is used to crop and label key morphological regions including plant leaves, stems and fruits. These extracted visual features serve as effective input information for training the growth stage classification model.

3.3. Weather-based irrigation correction

Because the actual soil moisture is affected by environmental changes, the study applies dynamic correction to I_{basic} in order to get the actual irrigation amount needed (I_{need}):

$$I_{need} = K_w \cdot (I_{basic} - I_{PID}) \quad (1)$$

In Equation (1), K_w is the weather correction coefficient; I_{PID} is the correction irrigation amount from PID correction.

The weather correction coefficient of K_w was determined according to the forecasted weather conditions for the following day, as summarized below:

- $K_w = 1.3$ for sunny days with high temperature ($T \geq 30^\circ C$);
- $K_w = 0.7$ for cloudy days, low-temperature days ($5^\circ C \leq T \leq 14^\circ C$), or light rain;
- $K_w = 0.5$ for rainstorms;
- $K_w = 1.0$ for sunny or cloudy days with moderate temperature ($15^\circ C < T < 30^\circ C$).

3.4. PI-based irrigation correction

PID algorithm is applied to correct the small variation. First, the study defines error $e(t) = \Delta H_{real} - \Delta H_{base}$. Where ΔH_{real} is the real ΔH , ΔH_{base} is the corresponding ΔH for the ideal irrigation amount.

The basic PID correction model for this irrigation system can be expressed by:

$$u(t) = K_p \bullet e(t) + K_i \bullet \int e(t) dt + K_d \bullet \frac{de(t)}{dt} \quad (2)$$

In Equation (2), $u(t)$ is the correction coefficient, K_p is proportional gain, K_i is integral gain, K_d is derivative gain, t is the cycle index, $\int e(t) dt$ is the accumulation of error.

Because the error is not very significant, this study ignores the derivative term, so the model can be simplified into:

$$I_{PID} = K_p \bullet e(t) + K_i \bullet \int e(t) dt \quad (3)$$

In Equation (3), I_{PID} is the correction irrigation amount from PID correction, $\int e(t) dt$ is the error accumulated for 3 days.

K_p represents how much the irrigation amount should increase when ΔH increases for 1%. The integration gain is thus defined by $K_I = K_p/3$, which is empirical ratio in PID turning. The value of K_p can be determined by finding the inverse of slope of I vs ΔH diagram during the steadily

increasing segment. Therefore, the value of K_p can be expressed by $K_p = \frac{dI}{d(\Delta H)}$, and the value of K_I is $K_i = \frac{K_p}{3}$.

Specifically, if the calculated I_{need} is negative, it represents the irrigation is excess, so I_{need} will be zero.

3.5. Scale ratio calculation and RLS-based adaptation

To enable adaptive deployment in new planting environments, the user firstly waters once with the I_{base} from the study's pot experiment result, and the system will measure the corresponding ΔH_{user} . The new basic irrigation amount is $I_{base_user} = I_{base} \cdot \frac{\Delta H_{base}}{\Delta H_{user}}$.

In addition, the proportional gain K_p is adjusted by RLS recursion. According to the ΔH vs I diagram provided in Section 4.1, because all of the ΔH vs I_{base} diagrams have coefficient of determination R^2 greater than 0.80 in these ideal increasing intervals, their relationship can be described as $I(t) = K_p(t) \cdot \Delta H(t) + \varepsilon(t)$, where $\varepsilon(t)$ is the prediction error.

The scalar form of the RLS recursions is used because only a single parameter needs to be estimated, offering a balance between computational simplicity and adaptive performance [14]. The recursions are as follows:

Initialization: The initial estimate of proportional gain was set to $\widehat{K}_p(0) = K_p$, where K_p was obtained from Table 3. The forgetting factor was assigned as $\lambda = 0.95$, and the initial uncertainty was set to $P(0) = 10$.

$$\begin{cases} \varepsilon(t) = I(t) - \widehat{K}_p(t-1) \cdot \Delta H(t) \\ G(t) = \frac{P(t-1) \cdot \Delta H(t)}{\lambda + P(t-1) \cdot [\Delta H(t)]^2} \\ \widehat{K}_p(t) = \widehat{K}_p(t-1) + G(t) \cdot \varepsilon(t) \\ P(t) = \frac{P(t-1) - G(t) \cdot \Delta H(t) \cdot P(t-1)}{\lambda} \end{cases} \quad (4)$$

In Equation (4), $G(t)$ is the gain, determining how much the system can trust the new data; $\widehat{K}_p(t)$ is the updated estimate of K_p ; $P(t)$ is the uncertainty (variance) of the estimate; λ is the forgetting factor. The core logic of the recursion is that $P(t)$ represents the system's confidence in its current estimate. An increase of $P(t)$ increases $G(t)$, allowing more correction of $\widehat{K}_p(t)$, while decrease of $P(t)$ reflects the improve of confidence.

3.6. Irrigation duration calculation

The study uses a float water tank to control flow velocity. According to Torricelli's principle, the outlet flow velocity can be expressed by $v = \sqrt{2gh}$, and the volumetric flow rate can be expressed by $Q = v \cdot A$, where v is the flow velocity at the outlet (m/s); g is gravitational acceleration (9.8 m/s^2); h is the vertical height between outlet and pot (m); Q is the volumetric flow rate (mL/s); A is the cross-sectional area of the outlet (m²). Therefore, the time length of pumping is $t = \frac{I_{need}}{Q}$.

3.7. Summary

The proposed method includes four sequential steps. After soil moisture differences (ΔH) and plant images are collected through pot experiments, the ΔH verses I diagrams for each stage of each plant are plotted. Second, the basic irrigation amount (I_{base}) is selected as the midpoint of the steadily increasing ΔH interval after eliminating unstable data. Third, the actual irrigation needed (I_{need}) is obtained by applying weather and PI-based corrections to I_{base} . Fourth, the system adapts to new environments by scale ratio calculation for new basic irrigation amount (I_{base_user}) and RLS-based recursive updates of the proportional gain (K_p). Last, the irrigation duration is calculated using Torricelli's principle. The water saving rate is then calculated to evaluate the irrigation system performance.

4. Experiment

This pot experiment was designed to explore the correlation investigate the relationship between irrigation amount and soil moisture difference and collect images for AI training. The independent variable was daily irrigation amount (I). The dependent variables were soil moisture difference (ΔH).

4.1. Material and equipment

Tomato and spinach were selected typical fruit vegetables and leafy vegetables for the experiment.as representative fruit and leafy vegetable crops. Fifteen seeds of each species were prepared, with five backups per species. Plants were grown in identical plastic pots (diameter 11 cm, height 13 cm) filled with nutrient soil under consistent conditions (23°C, natural sunlight). A USB camera captured plant images. Algorithm development used Python and Roboflow [13]. The physical system (Raspberry Pi 4B, pump, float tank) was specified but not constructed.

4.2. Planting and pot-experiment setup

Firstly, seeds were immersed in water for 24 hours, covered with moist tissue, and left to germinate. Seedlings were transplanted into 20 pots at 0.5 cm depth and irrigated with 30 mL/day until true leaves emerged.

Table 1. Irrigation amount in each growth stage for tomato and spinach

Crop	Growth stage	Irrigation amount (I , ml/day)
Tomato (T)	Seedling (S)	10, 20, 30, 40, 50, 60, 70, 80, 90, 100
Tomato (T)	Flowering (F)	60, 70, 80, 90, 100, 110, 120, 130, 140, 150
Tomato (T)	Fruiting (FR)	130, 140, 150, 160, 170, 180, 190, 200, 210, 220
Spinach (S)	Seedling (S)	20, 25, 30, 35, 40, 45, 50, 55, 60, 65
Spinach (S)	Rapid Growth (R)	60, 70, 80, 90, 100, 110, 120, 130, 140, 150

In Table 1, ten irrigation gradients were set for each growth stage, covering insufficient, moderate and excessive irrigation conditions.

When the growth condition of plants becomes stable, soil moisture sensor is inserted 3 cm from the stem, which corresponds to the most active root water absorption zone. The sensor's readings

before and 24 hours after watering for each pot are recorded. The moisture differential was calculated as $\Delta H = H_{final} - H_{initial}$.



Figure 2. Tomatoes and spinach in pot experiment: (a) tomato; (b) spinach (photo credit: original)

Figure 2 shows 10 tomato seedlings and 10 spinach seedlings are planted in identical pots on the balcony, each labeled with crop type, group number and corresponding irrigation volume.

A total of 150 images were collected for each crop in every growth stage. To enrich dataset diversity and improve model generalization ability, images were captured from multiple angles under varying ambient light conditions.

At the end of the tomato cycle, irrigation amount was reduced to induce drought stress. Spinach was continued to grow until heading. Both stress conditions were photographed with 150 images. This treatment was designed to build datasets for abnormal growth identification.

4.3. Results

Table 2. I_{base} in different growth stages for tomato and spinach

Growth stages	I_{base} (mL)
tomato seedling	55mL
tomato flowering	85mL
tomato fruiting	175mL
spinach seedling	45mL
spinach rapid growth	110mL

Table 2 summarizes the I_{base} found in pot experiment for each growth stage of each plant. I_{base} increases steadily as the plant grows.

Raw data of the soil moisture and irrigation amount at different growth stages is shown:

Table 3. Soil moisture data and irrigation amount for tomato seedling stage

I (mL)	10	20	30	40	50	60	70	80	90	100
$H_{initial}$	8.3	9.1	17.2	44.5	41.2	30.7	34.6	29.7	42.4	39
H_{final}	8.5	6.6	13.7	44.8	43	32.2	39.7	34.6	41.2	31.5
ΔH	0.2	-2.5	-3.5	0.3	1.8	1.5	5.1	4.9	-1.2	-7.5

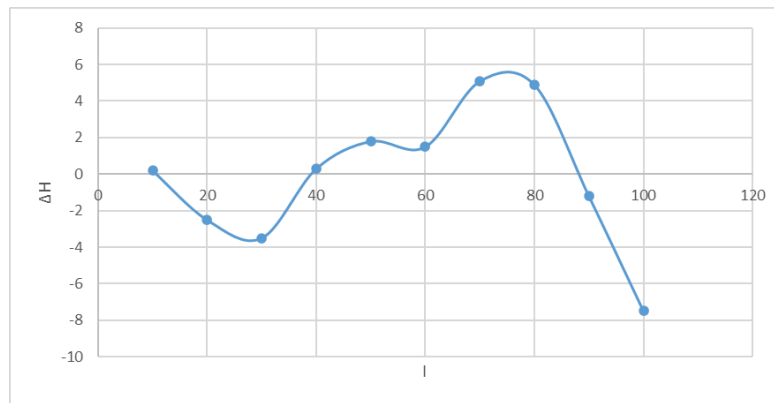


Figure 3. ΔH vs. I for tomato seedling stage ($R^2=0.88$) (photo credit: original)

Table 4. Soil moisture data and irrigation amount for tomato flowering stage

I (ml)	60	70	80	90	100	110	120	130	140	150
$H_{initial}$	17.4	17.8	10.4	9	13.3	27.9	6.1	14.5	9.3	19.6
H_{final}	18.7	20.7	15.3	14	21	36.9	6.1	19.7	8.9	29.4
ΔH	1.3	2.9	4.9	5	7.7	9	0	5.2	-0.4	9.8

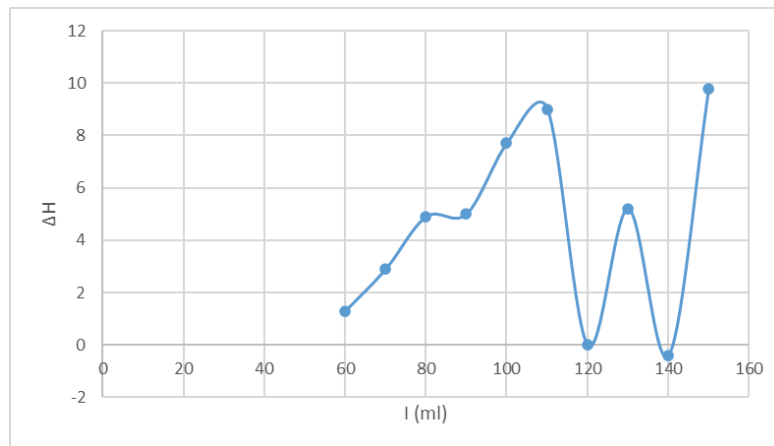


Figure 4. ΔH vs. I for tomato flowering stage ($R^2=0.97$) (photo credit: original)

Table 5. Soil moisture data and irrigation amount for tomato fruiting stage

I (mL)	130	140	150	160	170	180	190	200	210	220
$H_{initial}$	39.4	38.4	43.3	42.1	29.4	7.2	21.2	15.1	7.3	25
H_{final}	40.1	35.5	43.7	42.5	33.5	13.9	30.4	23.4	18.2	33.7
ΔH	0.7	-2.9	0.4	0.4	4.1	6.7	9.2	8.3	10.9	8.7

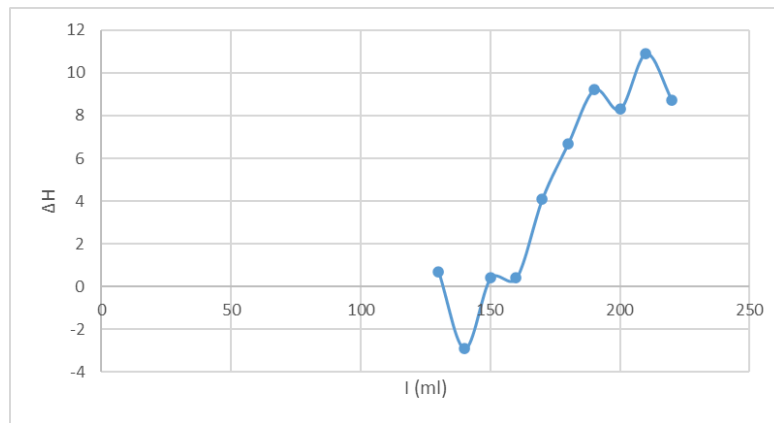


Figure 5. ΔH vs. I for tomato fruiting stage ($R^2=0.95$) (photo credit: original)

Table 6. Soil moisture data and irrigation amount for spinach seedling stage

I (mL)	20	25	30	35	40	45	50	55	60	65
$H_{initial}$	17.9	25.9	23.3	35.2	31.5	37.6	33.5	28.6	39.8	25.4
H_{final}	14.1	23.9	23.6	35.6	32.8	39.7	36.5	33.4	38.8	24.4
ΔH	-3.8	-2	0.3	0.4	1.3	2.1	3	4.8	-1	-1

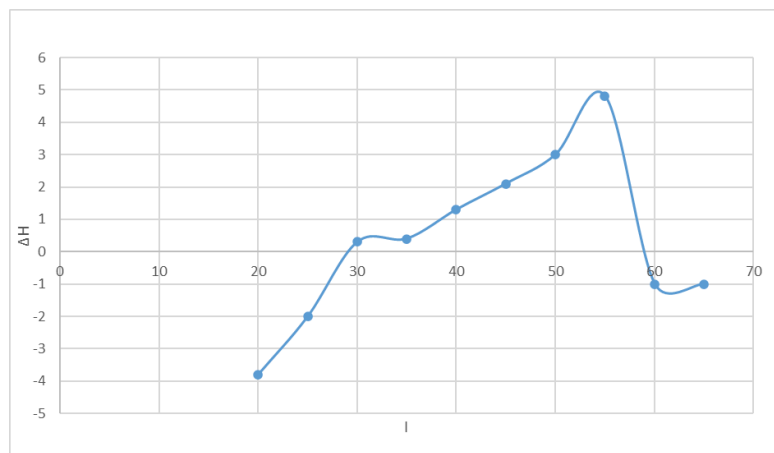


Figure 6. ΔH vs. I for spinach seedling stage ($R^2=0.96$) (photo credit: original)

Table 7. Soil moisture data and irrigation amount for spinach rapid growth stage

I (mL)	60	70	80	90	100	110	120	130	140	150
$H_{initial}$	36.1	43.8	37.4	42.5	35.1	36.7	40.3	40.2	38.3	39.7
H_{final}	36.7	44.8	41.6	43.1	38	40.5	43.5	44	44.3	40.5
ΔH	0.6	1	4.2	0.6	2.9	3.8	3.2	3.8	6	0.8

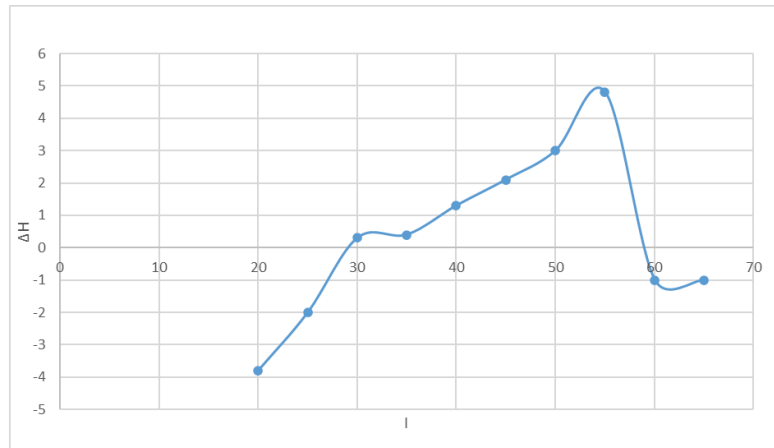


Figure 7. ΔH vs. I for spinach rapid growth stage ($R^2=0.80$) (photo credit: original)

In Table 3 to Table 7 and Figure 3 to Figure 7, the optimal stable interval yielded R^2 values above 0.80 for all growth stages. All the chosen I_{base} values are at the middle point of the steadily increasing interval of ΔH vs I_{base} graph.

Then, the corresponding values of K_p and K_i for each plant in each growth stage is calculated:

Table 8. Values of K_p and K_i in different growth stages for tomato and spinach

Growth stages	K_p (mL/%)	K_i (mL/%)
tomato seedling	4.65	1.55
tomato flowering	6.49	2.16
tomato fruiting	4.76	1.59
spinach seedling	4.54	1.52
spinach rapid growth	9.26	3.09

In Table 8, K_p is the inverse of the slope for ΔH vs I graph, and K_i is one third of K_p .

The YOLO model was applied to identify crop growth stages and water-stressed abnormal states. The training loss and validation accuracy is shown.



Figure 8. Training loss and validation accuracy results: (a) training loss; (b) validation accuracy (photo credit: original)

In Figure 8, the continuously decreasing training loss and 100% validation accuracy verify the reliability and stability of the model under controlled experimental conditions.

Table 9. 7-day dynamic irrigation correction (simulated data)

Day	Weather	Temperature (°C)	K_w	$\Delta H(\%)$	$H(\%)$	$e(t)$	$\int e(t)$	$I_{PID} (mL)$	$I_{need} (mL)$
1	sunny	24	1.0	2.7	32.7	0.0	0.0	0.0	55
2	sunny	25	1.0	1.0	33.7	-1.7	-1.70	-10.54	65.54
3	rainstorm	16	0.7	4.2	37.9	1.5	-0.20	6.67	33.83
4	light rain	17	0.5	5.0	42.9	2.3	2.10	13.95	20.53
5	sunny	23	1.0	1.5	44.4	-1.2	2.6	-1.55	56.55
6	cloudy	18	0.7	3.0	47.4	0.3	1.4	3.57	36.00
7	sunny	22	1.0	2.0	49.4	-0.7	-1.6	-5.74	60.74

Table 9 presents a 7-day simulation under typical spring monsoon climate. In this simulation, $K_p = 4.65ml/\%$; $K_i = 1.55ml/\%$; $I_{base} = 55ml$; $\Delta H_{base} = 2.7\%$.

A 15-day simulation ($K_w = 1$, $\Delta H_{target} = 5\%$, $noise \pm 0.2$) assumed true gain $K_p^* = 9.0$.

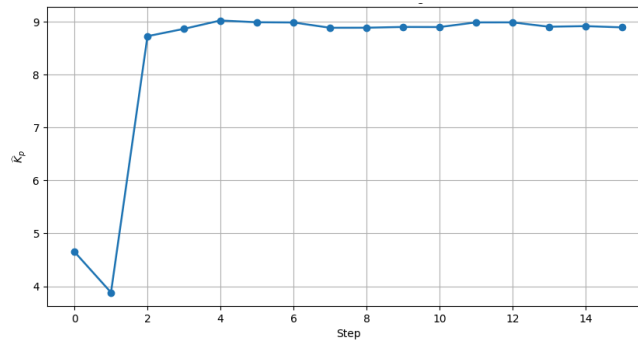


Figure 9. Convergence diagram of simulated K_p after correction (photo credit: original)

In Figure 9, $\widehat{K}_p(t)$ converges to 9.0 from 4.65 within about 5 days. Simulation results show that the RLS algorithm can rapidly converge and adapt the new K_p in a simulated new environment. The raw data of 15-day RLS simulation data is shown:

Table 10. Raw data of the 15-day RLS simulation (simulated data)

Step	$I (mL)$	$\Delta H (\%)$	$\widehat{K}_p$
1	0.00	-0.137	3.8841
2	19.95	2.259	8.7299
3	23.93	2.669	8.8692
4	20.68	2.199	9.0278
5	25.29	2.832	8.9948
6	19.50	2.173	8.9917

Table 10. (continued)

7	25.42	2.957	8.8913
8	18.16	2.041	8.8921
9	26.31	2.935	8.9065
10	18.39	2.070	8.9042
11	26.09	2.746	8.9921
12	20.27	2.252	8.9928
13	24.71	2.934	8.9102
14	18.41	2.028	8.9215
15	26.51	3.030	8.8982

Table 10 gives the raw data that the study used in RLS simulation and draw the convergence diagram, including I , ΔH and $\widehat{K_p}$ in each step.

The study assumes $h = 0.2m$, and $r = 0.002m$. The area of the water outlet is $A = \pi r^2 = 0.000013 m^2$. According to Torricelli's principle, the outlet flow velocity is $v = \sqrt{2gh} = 1.9799 m/s$, which gives $Q = v \cdot A = 2.513 \cdot 10^{-5} m^3/s = 25.13 ml/s$. Thus, irrigation time is: $t = \frac{I_{need}}{Q} = \frac{I_{need}}{25.13 ml/s}$.

In the 7-day simulated data (Table 4), $I_{corrected}$ is 328.19mL. If basic irrigation amount 55mL is applied every day, $I_{uncorrected}$ will be 385mL. Therefore, $Water Saving Rate = \frac{I_{uncorrected} - I_{corrected}}{I_{uncorrected}} = 14.8\%$.

4.4. Discussion

The ΔH method was used to determine I_{base} for each crop and growth stage. Because ΔH can represent the value of $I - E - A$, a steadily increasing ΔH over an irrigation interval indicates effective water utilization. Experimental data across all growth stages presented a three-stage variation trend, which verifies that this method is only valid within a reasonable irrigation range.

AI image recognition on Roboflow achieved 100% classification accuracy on the test set. Limited image samples per category were still sufficient for accurate identification under stable and controlled laboratory conditions.

The weather API provided macroscopic irrigation adjustment according to real-time meteorological conditions, and the PID controller realized microscopic feedback correction. The 7-day simulation verified the effectiveness of the PI control strategy. The derivative term was omitted to prevent environmental noise amplification. Furthermore, the RLS algorithm was adopted for real-time K_p parameter identification, which completed stable convergence within five days.

The main uncertainty sources include sensor measurement noise, the nonlinear I and ΔH relationship between irrigation volume and soil moisture variation, and the limitation of simulation-based data. Further research will focus on practical field validation to optimize the system.

5. Conclusion

The study establishes a household intelligent irrigation system model with tomato and spinach as experimental crops. Simulation shows that the model achieves a water-saving rate of 14.8%. The study verifies the possibility of combining basic electronic modules with algorithms control in household irrigation model design.

First, the study used ΔH method with pot experiment and successfully determined optimal I_{base} for tomato and spinach across five growth stages by selecting midpoint of stable rising interval of ΔH vs I diagram.

Second, the study used YOLOv8 model with AI image recognition technology with 105 annotated images per classification and achieved reliable classification of crop varieties and growth stages. The declining training loss and stable 100% validation accuracy fully prove the reliability and practicality of the YOLOv8 model in this task.

Third, the study used weather API integration and PID algorithm to realize environment-adaptive irrigation adjustment. When the system is applied in a new environment, the study applied scale ratio and RLS recursion to adjust the new I_{base} and adapt new gains. A 7-day PID simulation and a 15-day RLS simulation demonstrate the ability of the irrigation system to respond to environmental changes.

In addition, this study applied Torricelli's theorem to convert optimized irrigation volume into controllable irrigation duration. The calibrated water flow rate was 25.13 mL/s, enabling precise program-based irrigation timing control.

This study still has several limitations. First, all potted experiments were conducted only in spring, while baseline irrigation demands vary significantly across seasons. Second, this study did not record detailed crop growth indicators, including plant height, leaf area and biomass. Third, the system depends on real-time network access for weather API data, which restricts its offline application. Finally, the irrigation algorithm is currently verified only through experimental data and simulation results.

Future research will supplement experiments in different seasons and environmental scenarios to improve the universality of irrigation parameters. In addition, the system model can be further extended to more crop varieties. Moreover, the physical irrigation device and circuit system will be assembled and optimized based on the proposed operational logic, realizing physical deployment and practical verification of the intelligent irrigation system.

References

- [1] Zia, H., Rehman, A., Harris, N. R., Fatima, S., & Khurram, M. (2021). An experimental comparison of IoT-based and traditional irrigation scheduling on a flood-irrigated subtropical lemon farm. *Sensors*, 21(12), 4175. <https://doi.org/10.3390/s21124175>
- [2] Gu, Y., Jiang, L., & Liu, Z. J. (2025). Nongye guangai jishu fazhan xianzhuang yu zhanwang [Current status and prospects of agricultural irrigation technology development]. *Journal of Smart Agriculture*, 5(20), 40-44. <https://doi.org/10.20028/j.zhnydk.2025.20.010>
- [3] U.S. Environmental Protection Agency. (2016). *WaterSense specification for soil moisture-based irrigation control technologies*. <https://www.epa.gov/watersense>
- [4] Liu, C., Gong, B. B., Gao, H. B., et al. (2022). Jiyu zhengfamin zhengfaliang de yekang penzai fanqie shiyi guangailiang gusuan yu Shiyen [Estimation and experiment of the suitable irrigation amounts of potted tomatoes with coconut bran using pan evaporation]. *Journal of Agricultural Engineering*, 38(11), 117-124.
- [5] Wang, X. (2024). Jiyu STM32 de nongye Zhihui wulian guangai xitong sheji yu shixian [Design and implementation of an agricultural smart IoT irrigation system based on STM32]. *Computer Knowledge and Technology*, 20(26), 4-6.

- [6] Wu, X. (2025). PLC yu wulianwang mokuai zai zhineng guangai xitong zhong de xietong kongzhi sheji-yi wenshi fanqie guangai weili [Collaborative control design of PLC and Internet of Things module in intelligent irrigation system: A case study of greenhouse tomato irrigation]. *China Agricultural Machinery Equipment*, (12), 122-124.
- [7] Abdelmoneim, A. A., Kimaita, H. N., Al Kalaany, C. M., Derardja, B., Dragonetti, G., & Khadra, R. (2025). IoT sensing for advanced irrigation management: A systematic review of trends, challenges, and future prospects. *Sensors*, 25(7), 2291. <https://doi.org/10.3390/s25072291>
- [8] Qu, D. H. (2025). Gaobiaozhun nongtian jianshe zhong zhineng jieshui guangai xitong de sheji yu yingyong [Design and application of an intelligent water-saving irrigation system in the construction of high-standard farmland]. *Southern Agricultural Machinery*, 56(10), 123-126.
- [9] Cai, C. J., An, M. Y., Wu, H. K., Fang, X. Y., & Li, X. N. (2025). Jiyu AI shendu xuexi jishu de nongtian guangaishui youxiao liyong xishu cesuan fangfa chutan [Preliminary exploration of the calculation method for the effective utilization coefficient of farmland irrigation water based on AI deep learning technology]. *Journal of Anhui Agricultural Sciences*, 53(21), 201-205.
- [10] Sowby, R. B., & Lunstad, N. T. (2023). Why is residential irrigation so hard to optimize? *Water*, 15(18), 3177.
- [11] Lin, Y.-B., Lin, Y.-W., Lin, J.-Y., & Hung, H.-N. (2019). Sensortalk: An IoT device failure detection and calibration mechanism for smart farming. *Sensors*, 19(21), 4788.
- [12] Wang, Q., Zhang, P., Wu, H., Wu, X., Pang, Y., & Wu, J. (2026). Sustainability-oriented analysis of different irrigation quotas on sunflower growth and water use efficiency under full-cycle intelligent automatic irrigation in the arid northwestern China. *Sustainability*, 18(3), 1398.
- [13] Dwyer, B., Nelson, J., Hansen, T., et al. (2026). Roboflow (Version 1.0) [Software]. Available from <https://roboflow.com>
- [14] Haykin, S. (1996). *Adaptive filter theory* (3rd ed.). Prentice Hall.