Embedded Bi-IoT Irrigation System Driven by Artificial Intelligence for Optimized Agricultural Water Management

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Abstract

Efficient management of water resources in agriculture is a major challenge, particularly in the face of climate change and increasing food demand. Traditional irrigation systems, often static and based on predetermined schedules, result in water wastage and reduced yields. This paper proposes a conceptual modeling approach for an embedded Bi-IoT irrigation system driven by Artificial Intelligence (AI), aiming to optimize water usage and improve agricultural productivity. We introduce a formal framework in which the system state is defined by a vector of environmental characteristics, the action corresponds to the quantity of water delivered, and the yield is modeled by a complex function (e.g., a neural network) trained on historical data. Although this work is still at a preliminary stage without finalized numerical results, it provides a solid theoretical basis for the future design of optimal and dynamic irrigation policies, leveraging IoT and AI technologies as well as reinforcement learning methods.

Keywords: Smart Irrigation, IoT, Artificial Intelligence, Reinforcement Learning, Optimization, Sustainable Agriculture

1. Traditional Approaches and Historical Results

Over the past decades, irrigation strategies have often relied on **fixed schedules**, where water is supplied at predetermined intervals regardless of real-time environmental conditions [1]. In some cases, *manual monitoring* of soil moisture or simple *weather-based estimates* have been used to slightly adjust the watering frequency [2].

These **classical methods** were comparatively easy to implement but showed significant drawbacks:

- **Water wastage:** Due to the static nature of schedules, excess water is frequently delivered, leading to run-off or deep percolation [3].

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- **Lower yields:** Under-watering or over-watering can stress plants and reduce overall crop productivity [4].

- **Limited adaptability:** Changes in weather patterns or soil variability are not accounted for, which leads to inefficiencies [5].

Nevertheless, these older approaches provided baseline results that can still be valuable for comparison. For instance, [3] reported an average water consumption reduction of about 5–10% by integrating *basic sensor feedback* compared to purely fixed schedules. However, yields remained sensitive to unforeseen weather changes and crop-specific needs.

1.1. Comparison with the Proposed Bi-IoT AI-Driven Irrigation

In contrast, our proposed method introduces:

1. **Real-time monitoring** of multiple environmental factors (temperature, soil humidity, salinity, etc.).
2. **Adaptive control** via AI-based decision-making, aiming to maximize yield while minimizing water use.
3. **Scalability and flexibility**, as the policy can be updated when new data becomes available or when new sensor types are added.

As a result, we expect:

- More significant **water savings** than the 5–10% reduction reported in earlier partial automation systems.

- Higher **yield stability** due to the dynamic adjustment of water delivery.

- Increased **resilience** to climate variability and changing agricultural conditions.

Although full numerical validation is pending, this conceptual framework lays the foundation for a fully integrated **Bi-IoT irrigation system** with advanced AI capabilities. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

2. Introduction

The scarcity of water resources, driven by climate change and population growth, demands optimal agricultural irrigation management [1, 2]. Traditional methods, often based on fixed schedules, do not account for environmental conditions or the variability of crop water requirements, resulting in significant waste and inefficiency.

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The integration of the Internet of Things (IoT) in agriculture enables real-time data collection (e.g., temperature, humidity, soil pH) [3, 4], while Artificial Intelligence (AI) provides tools for modeling and predicting crop behavior [5, 6, 7]. The IoT-AI coupling opens the door to dynamic and adaptive irrigation strategies, which adjust the amount of water delivered based on the current state of the system, thus maximizing yield while minimizing water consumption [8].

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3. Methodology & Illustrative Tables

In this section, we outline a potential methodology for investigating Bi-IoT irrigation systems and present two **illustrative** tables (Table 1 and Table 2) that highlight some key comparisons.

Table 1: (Table 2) Classification of older/traditional vs. AI-driven irrigation methods (illustrative).

Method	Characteristics	Pros/Cons
Fixed schedule	Water delivered at set intervals only	+ Simplicity - Potential over-watering
Manual monitoring	Farmer inspects soil visually	+ Low cost - High uncertainty
Sensor-based	Basic soil moisture triggers	+ More adaptive - Not fully optimized
Bi-IoT + AI	Real-time data + ML policies	+ Optimized usage - Complex setup

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Table 2: (Table 3) Example results comparing older vs. new approaches (fictitious data).

Method	Yield Increase (%)	Water Savings (%)	Ref.
Fixed schedule	+0%	0%	[1]
Manual adjust.	+5%	5%	[3]
Sensor-based	+10%	10%	[4]
Bi-IoT + AI	**+20%**	**15–25%**	Proposed

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4. Results and Discussion

In this section, we discuss potential outcomes and challenges in deploying Bi-IoT irrigation solutions. Recent work, such as [10], demonstrates the growing popularity of machine learning techniques in smart irrigation systems. The authors highlight that ML-based strategies generally outperform conventional approaches, but implementation details can vary significantly among different case studies.

4.1. Potential Gains in Yield and Water Efficiency

A key advantage of AI-driven irrigation is the ability to adapt in real time. By continually monitoring soil metrics, climate patterns, and plant health, the system can deliver water in the exact quantities needed. As shown in Table 2, even a simple sensor-based approach can yield moderate improvements, whereas a full-blown IoT/AI integration promises up to 20% yield increases and 15–25% water savings (fictitious example).

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4.2. Implementation Challenges

Despite these promising results, multiple challenges remain:

- **Infrastructure costs:** Setting up sensors, communication modules, and computing platforms may be expensive for small-scale farms.
- **Data quality:** Biased or noisy sensor data can hamper the learning algorithms.
- **Scalability:** Ensuring real-time decisions across large farmlands with heterogeneous conditions requires robust network architecture.

Moreover, integrating AI-based decision-making with on-site agronomic practices demands cross-disciplinary expertise.

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5. Mathematical Modeling of the Proposed Method

Consider an agricultural field of size $n \times m$ (in m^2), containing p varieties of crops. This field is supplied by a water distribution network. Time is discrete, indexed by $t = 0, 1, \ldots, T$.

5.1. State and Environmental Characteristics

At each time step t, the environment is described by a state vector:

$$\theta_t = [\theta_t^1, \theta_t^2, \ldots, \theta_t^d] \in \mathbb{R}^d,$$

where the components θ_t^k represent the characteristics measured by sensors. For example:

$$\theta_t = [T_t, H_t, \mathrm{pH}_t, S_t, N_t, \ldots],$$

This vector can be enriched with climatic data (e.g., rainfall, temperature forecasts).

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5.2. Action and Decision Policy

At each time step t, the agent (the control system) must decide how much water to supply:

$$a_t = \psi(\theta_t, t) \geq 0,$$

where a_t is the water amount delivered between t and $t+1$. This decision can be derived from optimization algorithms or RL methods [9].

5.3. Yield and Modeling the Water-Yield Relationship

The agricultural yield at time t, denoted by Y_t, depends on environmental conditions and the chosen action. We consider a function (trained via an AI model):

$$Y_t = f(\theta_t, a_t; w),$$

where w represents the model parameters. The function f captures the complex relationship between environment, water input, and yield [5].

5.4. Objective Function and Optimization

We define a reward:

$$R_t = \alpha Y_t - \beta a_t,$$

with $\alpha > 0$ and $\beta > 0$. We seek a policy ψ^* that maximizes:

$$\psi^* = \arg\max_\psi \mathbb{E}\Big[\sum_{t=0}^{T} R_t\Big].$$

Solving the problem involves estimating f (supervised learning) and optimizing ψ (RL).

6. Future Work and Conclusion

At this stage, the modeling is conceptual and the function f remains to be estimated from real or simulated data. Future work will include:

- Collecting extensive field data to train f,
- Applying reinforcement learning algorithms (e.g., Q-learning, SARSA, deep RL) to find the optimal policy,
- Extending the approach to larger-scale farmland to study scalability,
- Integrating advanced sensors (e.g., multispectral imaging) for richer environmental feedback.

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Ultimately, this preliminary study underscores how Bi-IoT architectures, powered by AI, can enhance agricultural sustainability. Adopting these strategies should lead to robust water savings and yield improvements, helping address the growing challenges of food demand and climate change.

CRediT authorship contribution statement

Youssef Balouki: Conceptualization, Writing - Original Draft, Formal Analysis, Editing.
Imane Lmati: Methodology, Review.
Youssef Zarouali: Supervision, Review & Editing.

Declaration of competing interest

The authors declare no conflict of interest.

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References

[1] FAO, "Water for Sustainable Food and Agriculture: A report produced for the G20 Presidency of Germany," Food and Agriculture Organization of the United Nations, 2017.

[2] IPCC, "Climate Change 2014: Synthesis Report," Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 2014.

[3] Y. Kim, R. G. Evans, W. M. Iversen, “Remote Sensing and Control of an Irrigation System using a Distributed Wireless Sensor Network,” *IEEE Transactions on Instrumentation and Measurement*, vol. 57, no. 7, pp. 1379–1387, 2008.

[4] M. A. Shahid, M. N. Aslam, M. Hussain, “Internet of Things (IoT) Applications in Smart Agriculture: Issues, Challenges, and Opportunities,” *IEEE Access*, vol. 9, pp. 37876–37890, 2021.

[5] J. Li, G. Hoogenboom, R. W. McClendon, “Improving Evapotranspiration Estimates by Combining a Two-Source Model and AI-Based Approaches,” *Agricultural Water Management*, vol. 98, no. 3, pp. 507–518, 2011.

[6] C. Y. Yeun, “AI-Enabled IoT Systems in Smart Agriculture,” In: *Intelligent Computing & Optimization*, Springer, pp. 857–867, 2020.

[7] A. Tagarakis, D. Bochtis, T. Fountas, P. Ketikidis, “Internet of Things (IoT) in Agriculture—Recent Advances and Future Challenges,” *Agriculture*, vol. 11, no. 6, p. 541, 2021.

[8] D. Tang, B. C. McCarthy, D. Z. Pan, “Internet of Things (IoT) and Artificial Intelligence (AI) in Agriculture: An Emerging Paradigm,” *IEEE Internet of Things Journal*, 2021 (early access).

[9] S. Zhang, W. Xiao, L. Cheng, “Deep Reinforcement Learning for Smart Irrigation: A Simulation Study,” *IEEE Access*, vol. 8, pp. 160420–160430, 2020.

[10] A. Younes, Z. Elamrani Abou Elassad, O. El Meslouhi, D. Elamrani Abou Elassad, E. Abdel Majid, “The application of machine learning techniques for smart irrigation systems: A systematic literature review,” *Smart Agricultural Technology*, 7 (2024) 100425.