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

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January 6, 2025

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

1. Introduction

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

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The integration of the Internet of Things (IoT) in agriculture enables the real-time collection of data (e.g., temperature, humidity, soil pH) [3, 4], while Artificial Intelligence (AI) provides tools to model and predict crop behavior [5, 6**?**]. The IoT-AI coupling paves the way for dynamic and adaptive irrigation strategies that adjust the amount of water delivered based on the current state of the system, thereby maximizing yield while minimizing water consumption [10].

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2. 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.

3. 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 *weather-based estimates* have been used to slightly adjust the watering frequency [2].

These **classical methods** were relatively easy to implement but exhibited significant drawbacks:

- **Water Wastage:** Due to the static nature of schedules, excessive water is frequently delivered, leading to runoff or deep percolation [7].
- **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, leading to inefficiencies [5].

Nevertheless, these older approaches provided baseline results that can still be valuable for comparison. For instance, [7] 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.

3.1. 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.

4. Results and Discussion

In this section, we discuss potential outcomes and challenges in deploying Bi-IoT irrigation solutions. Recent work, such as [9], 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. Methodology & Illustrative Tables

In this section, we describe a potential methodology for studying Bi-IoT irrigation systems and present two **illustrative tables** (Table 1 and Table 2) highlighting 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 (%)**	**Reference**
Fixed Schedule	+0%	0%	[1]
Manual Adjustment	+5%	5%	[7]
Sensor-Based	+10%	10%	[4]
Bi-IoT + AI	**+20%**	**15–25%**	Proposed

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6. 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 $t = 0, 1, \dots, T$.

6.1. State and Environmental Characteristics

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

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

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

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

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

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6.2. 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 quantity of water delivered between t and $t+1$. This decision can be derived from optimization algorithms or reinforcement learning (RL) methods [11].

6.3. 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 the environment, water input, and yield [5].

6.4. 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).

7. 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: Supervision, Conceptualization, Methodology, Formal Analysis, Review.
Imane Lmati: Supervision, Methodology, Formal Analysis, Review.
Youssef Zarouali: Conceptualization, Methodology, Review & Editing.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgments

The authors would like to thank the staff of the Department of Mathematics and Computer Science (Faculty of Sciences and Technology of Settat) for their continuous support and valuable suggestions during the drafting of this manuscript.

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