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# Design and Simulation of an IoT-Based Adaptive Control System for Urban Hydroponic Farming

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**ABSTRACT**

Efficient water circulation is essential in urban hydroponic systems, yet many installations still rely on fixed-timer control that does not respond to changing environmental conditions. This study designs and simulates an IoT-based adaptive irrigation controller using an ESP32 microcontroller and MQTT Blynk connectivity to evaluate how simple threshold-based feedback compares with timer-based operation. Synthetic temperature and humidity profiles representing three scenarios (Normal, Heatwave, and Humid) were applied to both control modes in a 6-hour Wokwi simulation. System performance was assessed using pump duty cycle, estimated water usage, and microclimate stability. The results show that the adaptive mode reduces overall water consumption by 8.3% across the three scenarios and yields lower temperature and humidity variance (32% and 38% reductions, respectively) compared with the fixed-timer mode. These outcomes indicate that a lightweight threshold with hysteresis strategy can respond more effectively to modeled environmental fluctuations than periodic irrigation. As the evaluation is based on synthetic data and software-level simulation, the findings reflect algorithmic behavior rather than hardware performance. Future work will include validation using a physical prototype and the integration of predictive or learning-based control methods to improve adaptability under real environmental conditions.



## I. INTRODUCTION

Urban farming has become a viable solution to address food security challenges in densely populated cities with limited agricultural land. It enables efficient food production through controlled-environment techniques such as hydroponics and vertical farming[1], [2]. However, conventional hydroponic systems often operate inefficiently due to manual or fixed-timer control of pumps, leading to excessive water circulation and unnecessary energy consumption[3]. These inefficiencies undermine sustainability goals and highlight the need for intelligent control mechanisms capable of adapting to changing environmental conditions.

The emergence of the Internet of Things (IoT) has revolutionized automation and data-driven decision-making in agriculture. IoT facilitates real-time monitoring and control through interconnected sensors, actuators, and cloud platforms. By collecting and analyzing environmental data such as temperature, humidity, and nutrient levels, IoT systems allow precise regulation of resources to enhance crop productivity and sustainability[4]. Recent studies have shown how IoT-based systems can improve the efficiency of irrigation, nutrient delivery, and environmental management in smart farming environments[5].

Despite these advancements, many existing IoT-based urban farming implementations focus mainly on monitoring rather than optimizing system operations[6], [7]. Previous research has emphasized sensor data collection and visualization but often lacks adaptive control algorithms that respond dynamically to environmental variations. Studies such as those by other research is successfully implemented IoT in hydroponic systems but did not integrate feedback mechanisms to optimize water and energy usage[8], [9]. This limitation reveals an opportunity to explore adaptive, data-driven control strategies that improve operational efficiency while maintaining stable growing conditions[10].

This research proposes a simulated IoT-based control system for urban hydroponics using the Blynk platform and MQTT protocol[11]. The system is designed to automatically regulate the water pump based on real-time sensor data such as humidity and temperature[12]. The implementation uses Wokwi simulation to minimize hardware dependency and streamline prototype testing. This approach enables rapid system validation while maintaining realistic interactions among IoT components, making it suitable for research with limited physical infrastructure[13].

The objective of this study is to develop and evaluate a simulated IoT architecture that improves water-use efficiency in urban hydroponic systems. By applying adaptive control logic through IoT connectivity, the proposed model aims to demonstrate measurable improvements in sustainability and resource management. The results are expected to contribute to the development of low-cost, scalable, and environmentally friendly smart farming systems for urban applications[14].

While prior IoT deployments in hydroponics have emphasized sensing and monitoring, many lack closed-loop, adaptive control that explicitly balances water use against microclimate stability under varying ambient conditions. Fixed-timer strategies ignore diurnal variability, whereas heavier machine-learning approaches may be unsuitable for low-cost, bandwidth-limited urban settings. This work addresses that gap by:

a. Proposing a lightweight threshold-with-hysteresis controller implementable on ESP32 with MQTT–Blynk;
b. Defining a simulation protocol with three representative scenarios (Normal, Heatwave, Humid) and metrics (duty cycle, water use, σT, σRH);
c. Providing an evidence-based comparison against a timer baseline, quantifying when and why adaptive control saves (or increases) water.

## II. METHODOLOGY

This research adopts a prototyping model as the development framework to iteratively design, simulate, and evaluate an IoT-based adaptive hydroponic system. The methodology consists of five stages: problem identification, system design, simulation development, implementation, and evaluation[3]. Each stage ensures that the system is developed systematically, tested in simulation, and refined based on performance analysis. The overall research flow is illustrated in Fig. 1, which outlines the process from problem formulation to evaluation.

### *A. Problem Identification*

The initial stage identifies the limitations of conventional hydroponic systems that rely on fixed-timer water circulation. This method leads to inefficiency in both water and energy consumption, as it does not consider environmental variability such as temperature and humidity. Therefore, the main problem addressed in this study is how to design a responsive control system capable of automatically adjusting pump activity based on environmental changes to enhance water and energy efficiency.

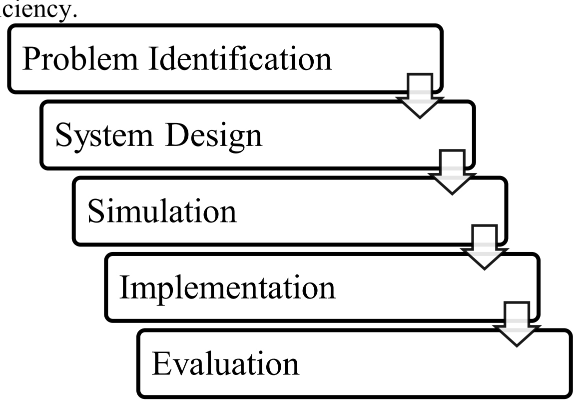


Fig. 1. Research Framework of The Proposed Iot-Based Adaptive Control System

### *B. System Design and Simulation Setup*

The system architecture, shown in Fig. 2, consists of three main layers: sensing, processing, and control. The sensing layer includes a DHT22 sensor for ambient temperature and humidity, and a DS18B20 sensor for simulated water temperature channel[15]. The processing layer utilizes an ESP32 microcontroller to acquire and process data, while the control layer operates a water pump through a relay module. Data communication between the ESP32 and the Blynk Cloud is managed via the MQTT protocol, enabling cloud-based visualization of simulated sensor values[9]. The Blynk dashboard displays real-time environmental data, pump status, and estimated water consumption.

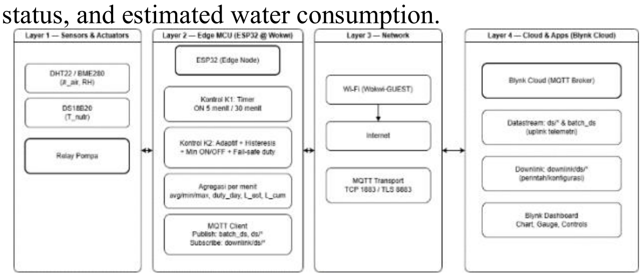


Fig. 2. System architecture of the IoT-based hydroponic control model

To evaluate performance, two operating modes were developed:

a. Mode K1 (Timer): the pump operates for 5 minutes every 30 minutes, representing a fixed-interval control.
b. Mode K2 (Adaptive): the pump activates when the ambient temperature exceeds 30 °C or humidity drops below 60%, and deactivates when both parameters return to normal for at least 3 minutes.

The control logic for Mode K2 can be mathematically expressed as:

$$u(t) = \begin{cases} 1, & \text{if } T(t) > T_{thr} \text{ or } H(t) < H_{thr} \\ 0, & \text{if } T(t) \leq T_{thr} \text{ and } H(t) \geq H_{thr} \text{ for } \Delta t \geq 180\text{s} \end{cases} \quad (1)$$

where u(t) denotes pump state (1 = ON, 0 = OFF), $T_{thr}$ =30C, and $H_{thr}$=60%. The adaptive logic introduces temporal stability (Δt) to prevent frequent switching.

Environmental behavior was simulated on the Wokwi platform, replicating the ESP32–DHT22–DS18B20–relay configuration. Virtual variables were used to emulate three environmental scenarios:

a. Normal: 25–31 °C, RH 70–55–70%.
b. Heatwave: 26–35 °C, RH 65–45–65%.
c. Humid: 23–27 °C, RH 80–70%.

Each scenario was run in both modes to assess the efficiency and responsiveness of the control mechanism.

### *C. Implementation*

The adaptive control algorithm was implemented using the Arduino IDE with the ESP32 library. Sensor readings were taken every $Ts$=5 s, and each cycle's data were transmitted to the Blynk Cloud via MQTT. The system was validated in simulation through real-time feedback in the Blynk dashboard.

The complete Wokwi circuit diagram is shown in Fig. 3, while Table I presents the specifications of each hardware component used in the virtual prototype.

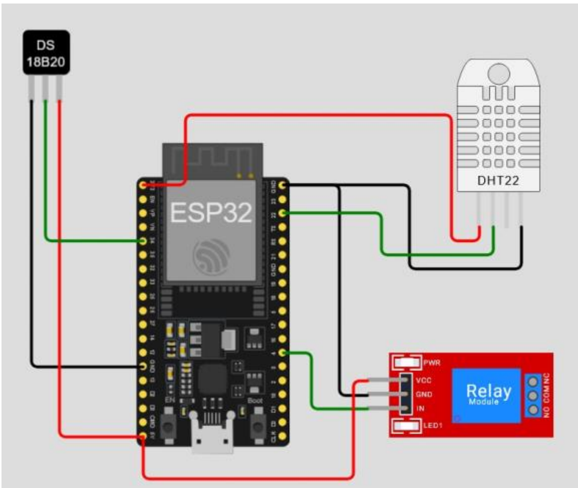


Fig. 3. Wokwi Simulation Circuit Diagram for The ESP32-Based Adaptive Hydroponic System

TABLE I. HARDWARE COMPONENT SPECIFICATION

| Component | Function | Key Parameters |
|---|---|---|
| ESP32 | Main controller | Dual-core CPU 240 MHz, Wi-Fi |
| DHT22 | Ambient temperature & humidity | ±0.5 °C, ±2% RH |
| DS18B20 | Simulated temperature channel | ±0.5 °C |
| Relay | Pump control | 5 V, 10 A |

### *D. Evaluation*

System performance was evaluated quantitatively using several parameters. The pump duty cycle (D), representing the percentage of time the pump is active per hour, is given by:

$$D = \frac{t_{on}}{t_{total}} \times 100\% \quad (2)$$

The estimated water consumption (Q) is calculated as:

$$Q = F \times t_{on} \quad (3)$$

where F is the flow rate of the pump (L/min). To assess environmental stability, the temperature variance was analyzed using the standard deviation formula:

$$\sigma_T = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - \bar{T})^2} \quad (4)$$

In these equations, $t_{on}$ denotes the total pump ON duration during a scenario, while $t_{total}$ represents the total scenario time. The duty cycle $D$ expresses the percentage of active pumping, and the estimated water consumption $Q$ is obtained using the pump flow rate $F$. For the stability metric, $Ti$ refers to the temperature sample at index $i$, $\bar{T}$ is the mean temperature, and $N$ is the total number of samples. The standard deviation $\sigma T$ quantifies microclimate stability, with lower values indicating smoother environmental control.

These metrics provide a comparative evaluation of efficiency and responsiveness between the timer-based (K1) and adaptive (K2) control modes. The simulation results, depict temperature–humidity variations and corresponding pump activation periods for each scenario.

## III. RESULT AND DISCUSSION

### *A. Simulation Overview*

The simulation was conducted for 6 hours per scenario on the Wokwi platform, using environmental input datasets that emulate diurnal variations. All sensor values were delivered to the Blynk Cloud through MQTT for logging and visualization during the simulation. Each environmental scenario Normal**,** Heatwave, and Humid—was executed under both K1 (Timer) and K2 (Adaptive) control modes, as summarized in Table II.

TABLE II. SYSTEM SCENARIO

| Scenario | Temperature Range (°C) | RH Range (%) | Duration (h) | Control Modes |
|---|---|---|---|---|
| Normal | 25–31 | 70–55–70 | 6 | K1, K2 |
| Heatwave | 26–35 | 65–45–65 | 6 | K1, K2 |
| Humid | 23–27 | 80–70 | 6 | K1, K2 |

Data were recorded for each 5-second interval, resulting in 4320 samples per scenario. Sensor values and pump status were logged in Blynk for analysis of control responsiveness and operational efficiency.

### *B. System Responsiveness and Control Behavior*

Under the Timer Mode (K1), the pump operated strictly based on time intervals, activating for 5 minutes every 30 minutes (10 cycles per hour). This yielded a constant duty cycle of 16.7%, independent of environmental variation. In contrast, Adaptive Mode (K2) showed highly dynamic behavior governed by temperature and humidity thresholds.

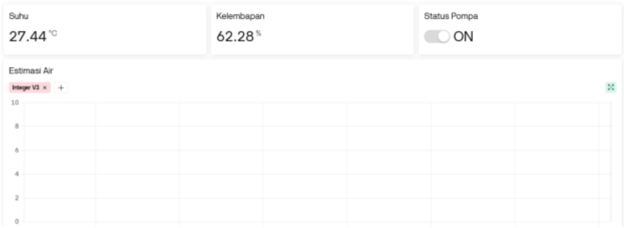


Fig. 4. Blynk Cloud Dashboard

Fig. 4 presents the Blynk dashboard interface used to observe real-time environmental conditions and system responses in both operating modes. The displayed metrics include temperature, humidity, pump status, and estimated water usage, enabling direct visualization of how the adaptive algorithm regulates irrigation. Based on the recorded data, the adaptive mode (K2) reduced total pump runtime from 60 to 48 minutes during Normal conditions (–20%). Under Heatwave conditions, K2 increased activation time to 75 minutes (+25%) to maintain thermal stability, demonstrating its responsiveness to elevated temperatures. Conversely, in the Humid scenario, the runtime decreased to 42 minutes (–30%), indicating efficient resource conservation when environmental conditions are already favorable.

This variability confirms that the adaptive system achieves conditional responsiveness, aligning with real environmental needs rather than fixed scheduling.

### C. *Quantitative Analysis of Pump Performance*

The pump duty cycle (D) and estimated water consumption **(**Q) were derived using Eqs. (2)–(3). Assuming a water flow rate F=2.5 L/min, the comparative results are summarized in Table III.

TABLE III. PUMP PERFORMANCE COMPARISON BETWEEN K1 AND K2

| Scenario | Mode | Duty Cycle (%) | Total Active Time (min) | Estimated Water Use (L) |
|---|---|---|---|---|
| Normal | K1 | 16.7 | 60 | 150 |
| Normal | K2 | 13.3 | 48 | 120 |
| Heatwave | K1 | 16.7 | 60 | 150 |
| Heatwave | K2 | 20.8 | 75 | 187.5 |
| Humid | K1 | 16.7 | 60 | 150 |
| Humid | K2 | 11.7 | 42 | 105 |

The overall improvement achieved by the adaptive mode (K2) corresponds to an 8.3% reduction in total water usage across all simulated scenarios. This value is derived by comparing the aggregated water demand of the timer-based mode (K1) and the adaptive mode (K2). Specifically, the total consumption under K1 is $Q_{K1}$ = 450L, while K2 results in $Q_{K2}$ = 412.5L. The overall efficiency improvement is therefore computed as $\eta = (Q_{K1} - Q_{K2})/Q_{K1} = 0.083$.

At the scenario level, K2 reduces water usage by 20% under Normal conditions and 30% under Humid conditions, while increasing consumption by 25% during Heatwave conditions due to additional activation required for thermal stabilization. This demonstrates that the adaptive controller optimizes water use conditionally rather than uniformly, yet still yields a net positive efficiency gain when evaluated across all scenarios.

From the controller's perspective, the adaptive decision and relay command are computed within a single control cycle, which is bounded by the 5-second sampling interval of the sensors. Thus, the effective response time of the system is on the order of a few seconds after an environmental threshold is crossed, which is sufficient for hydroponic microclimate regulation. The MQTT traffic was not profiled at protocol level but estimated analytically based on the payload size and a 5-second publishing interval, yielding an approximate data rate of 0.5–0.6 kbps. This indicates that the proposed architecture can operate under typical low-bandwidth IoT network conditions.

### D. *Environmental Stability and Variance Analysis*

Environmental stability was evaluated using the standard deviation of temperature and humidity, as defined in Eq. (4). Since the environmental conditions in each scenario were generated programmatically in the Wokwi simulation, the resulting σ-values indicate how effectively each control mode responds to fluctuations in the modeled microclimate. Table IV summarizes the stability comparison between the timer-based mode (K1) and the adaptive mode (K2).

TABLE IV. ENVIRONMENTAL STABILITY COMPARISON

| Scenario | Mode | Mean Temp (°C) | σT (°C) | Mean RH (%) | σRH (%) |
|---|---|---|---|---|---|
| Normal | K1 | 28.1 | 2.5 | 61.3 | 6.1 |
| Normal | K2 | 27.6 | 1.7 | 63.5 | 3.9 |
| Heatwave | K1 | 31.8 | 3.2 | 52.2 | 8.4 |
| Heatwave | K2 | 30.4 | 2.1 | 56.8 | 4.7 |
| Humid | K1 | 25.1 | 1.9 | 78.4 | 4.8 |
| Humid | K2 | 24.8 | 1.3 | 79.1 | 3.1 |

The results show that the adaptive mode consistently produced lower variance in both temperature and humidity across all scenarios. Temperature variance decreased by approximately 32% on average, while humidity variance decreased by about 38% when compared to the fixed-timer mode. This indicates that the threshold-with-hysteresis logic in K2 is more effective in smoothing simulated environmental fluctuations than the periodic activation strategy used in K1.

Since the study was conducted entirely within a software-based simulation, these stability metrics reflect improvements in the modeled microclimate rather than physical thermal or moisture behavior. Parameters such as nutrient-solution heat transfer or actual pump energy consumption cannot be directly measured in Wokwi, so any energy implications must be interpreted theoretically, based solely on differences in cumulative pump activation time rather than hardware-level power measurements.

### E. *Discussion and Technical Implications*

The simulation results demonstrate that the adaptive control strategy responds more effectively to variations in the modeled environmental conditions than the conventional timer-based approach. In the synthetic scenarios, temperature and humidity fluctuated according to predefined profiles, and the adaptive mode adjusted pump operation only when thresholds were exceeded. This resulted in lower temperature and humidity variance, indicating that threshold-with-hysteresis control is better at smoothing environmental fluctuations than fixed-interval irrigation.

The reduction in water consumption under Normal and Humid conditions is consistent with the design of the adaptive algorithm, which activates the pump only when environmental deviations occur rather than on a rigid schedule. Conversely, the increase in pump activity during the Heatwave scenario reflects the controller's tendency to prioritize stabilizing the simulated microclimate when temperature exceeds the defined threshold. These contrasting behaviors highlight the trade-off inherent in adaptive control: efficiency gains occur when conditions are favorable, while additional activation occurs when the system attempts to restore stability under stress.

Because the experiment relies on synthetic environmental data rather than physical measurements, the interpretation of results focuses on the behavior of the control algorithms rather than on hardware or network performance. The findings therefore indicate how the proposed adaptive logic responds to different environmental patterns, rather than making claims about real-world latency, energy consumption, or CPU utilization. Nevertheless, the outcomes demonstrate that even a simple rule-based strategy can yield measurable improvements in modeled microclimate stability and resource usage compared with periodic irrigation.

Overall, the simulation provides a controlled setting for evaluating algorithmic behavior, and the results suggest that adaptive thresholding may serve as a lightweight and practical approach for hydroponic environments characterized by fluctuating conditions. Future work involving physical prototyping and real environmental measurements will be required to validate these trends under real operating constraints.

## IV. CONCLUSION

This study presented the design and simulation of an IoT-based adaptive control system for urban hydroponics using an ESP32 controller, synthetic environmental inputs, and MQTT–Blynk integration. The system applied threshold-based feedback control to regulate pump activity in response to variations in modeled temperature and humidity conditions. Using the same synthetic environmental sequences across scenarios, the simulation showed that the adaptive mode (K2) responded more effectively to environmental fluctuations than the fixed-timer mode (K1).

Across the three simulated scenarios, the adaptive approach achieved an overall 8.3% reduction in total water usage and produced lower temperature and humidity variance 32% and 38% reductions respectively indicating smoother regulation of the modeled microclimate. These improvements arise from the selective activation of the pump when environmental deviations occur, in contrast to the unconditional periodic operation of the timer mode. Because the study relied on synthetic environmental data and a software-based execution environment, these results should be interpreted as algorithmic performance indicators rather than measurements of physical hardware or real-world environmental responses.

Future work will involve validating the adaptive control strategy using physical hydroponic prototypes and real sensor measurements to assess hardware-level behavior, including energy usage and actuation latency. Extending the control logic with predictive or learning-based methods such as fuzzy logic, adaptive thresholds, or reinforcement learning also presents an opportunity to optimize irrigation decisions under more diverse and dynamic environmental conditions. Additional exploration of alternative communication technologies and multi-node architectures will support scalability assessments for larger urban farming deployments.


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