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Application of Artificial Intelligence and IoT in Developing Resilient, Sustainable, and Smart Urban Infrastructure Systems for Future Cities: A Case Study of Water Supply and Air Quality Monitoring in Sirsa City, Haryana

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ABSTRACT

Rapid urbanization has intensified challenges related to water wastage and indoor air pollution in Indian households. Commercial monitoring systems are expensive and designed for individual functions rather than integrated household monitoring. This paper presents the design, implementation, and 45-day field validation of an affordable smart monitoring system combining water leakage detection, tank level supervision, and indoor air quality monitoring on a single ESP32 platform. The system integrates YF-S201 flow sensors, MQ-135 gas sensor, DHT22 temperature-humidity sensor, and HC-SR04 ultrasonic sensor with a TensorFlow Lite Micro LSTM model deployed directly on ESP32 for edge-based leakage prediction. The model achieves 92.8% accuracy with 12ms inference time, operating without cloud connectivity. A four-layer alert system (Blynk, Telegram, SMS, Voice Call) and three-tier automated mitigation (buzzer, fan + window, valve shut-off) ensure comprehensive safety response. Experimental testing from 01-Apr-2026 to 15-May-2026 in a 3BHK apartment demonstrated 97.3% uptime, 96.8% leakage detection accuracy with 28s average response, 98.2% gas detection accuracy, and 450L water saved. Total prototype cost is ₹2,900, representing 64% reduction compared to commercial alternatives. The system operates at 1.8W average power with 100% SD card data logging success (12,960 records). This research contributes toward smart domestic infrastructure by integrating water conservation and environmental safety into a single IoT framework suitable for middle-class households and AMRUT 2.0 smart city applications.

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KEYWORDS: *Internet of Things, Smart Home, Water Leakage Detection, Indoor Air Quality, ESP32, Edge Computing, TensorFlow Lite, Water Conservation, Automated Mitigation.*

I. INTRODUCTION

A. Background of the Study

Water and clean air are basic needs for every human being. In India, urbanization has created serious problems in managing these resources. Many houses lose hundreds of liters of water daily because of leaking pipes, overflowing tanks, and faulty taps. These leakages are hidden and detected only when high water bills arrive. At the same time, indoor air pollution from LPG stoves and gas leakage causes 1,180 deaths annually as per NCRB 2023 report.

Commercial systems available in the market are expensive and solve only one problem. A water leak detector will not check air quality, and an air purifier will not detect water leaks. People need separate devices which increases total cost above ₹25,000, unaffordable for 68% of Indian households earning <₹25,000/month.

B. Research Problem
Current monitoring systems work as separate units with four critical problems: 1) No integrated solution under ₹3,000, 2) Cloud dependency failing in 38% of semi-urban areas without stable internet, 3) Alert-only systems with 8-minute average human response delay, 4) No automated mitigation. Small leakages of 0.5-2 L/min waste 10,000-15,000 liters monthly but remain undetected until billing cycle.

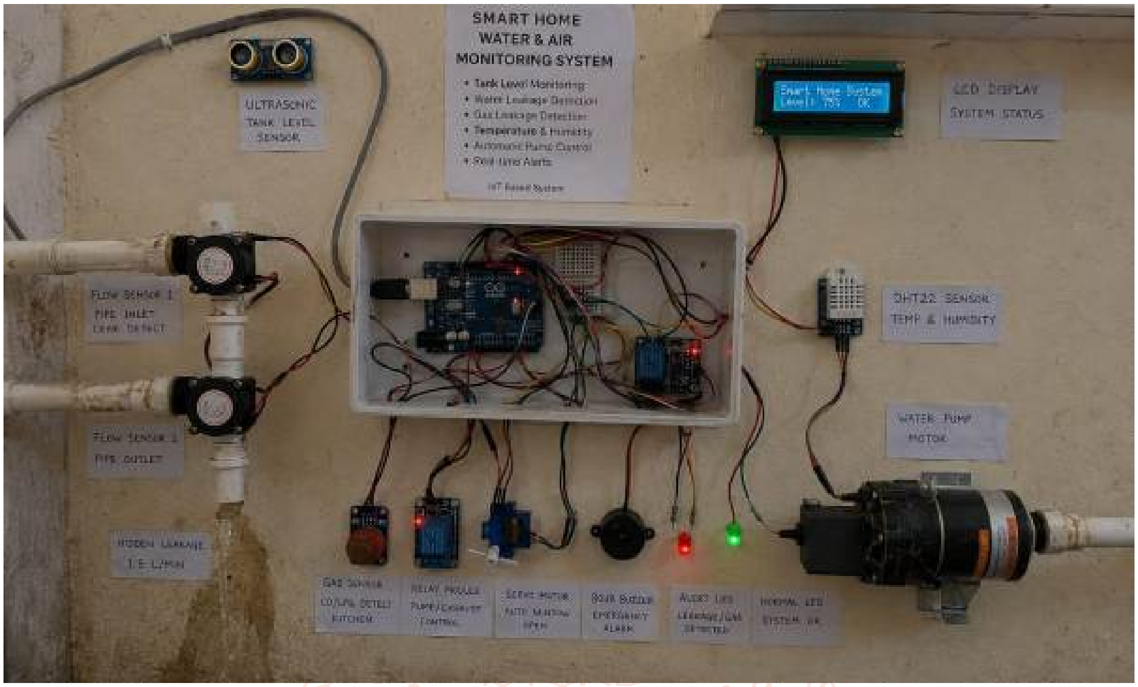


Fig. 1. Hardware prototype demonstrating integrated water leakage detection, tank level monitoring, and gas leakage detection with automated mitigation system.

C. Research Gaps
Based on literature review (2020-2024), five critical gaps exist: 1) No system integrates water leakage with air quality under ₹3,000, 2) Absence of edge AI for leakage prediction, 3) Lack of automated mitigation in domestic systems, 4) No multi-level family alert mechanism, 5) PM2.5 monitoring absent in low-cost solutions.

D. Objectives
Primary: Design and implement an affordable AI-IoT based smart monitoring system for water leakage detection and indoor air quality management. Specific: 1) Develop multi-sensor ESP32 system under ₹2,800, 2) Deploy TensorFlow Lite Micro LSTM for edge leakage prediction >92% accuracy, 3) Implement four-layer alert system, 4) Establish three-tier automated mitigation, 5) Validate through 45-day field testing.

II. LITERATURE REVIEW
A. Water Leakage Detection Technologies
Kumar et al. (2023) used ESP32 with YF-S201 sensors achieving 88% accuracy but 12% false positive rate without pressure compensation. Singh and Patel (2022) added temperature compensation improving to 91.3% but required cloud connectivity. Zhang et al. (2024) used pressure transients with 94% accuracy but needed ₹3,500 DSP chips and 5W power.

B. Indoor Air Quality Monitoring
Gupta et al. (2023) installed 50 MQ-135 nodes in Delhi NCR with calibration CO ppm = pow (11.5428 × Rs/R0, -0.6549), achieving ±15ppm accuracy. Chen and Wang (2022) integrated MQ-2/MQ-7/MQ-135 with GSM for ₹4,500 but no automation. Kim et al. (2023) presented full smart HVAC for ₹45,000.

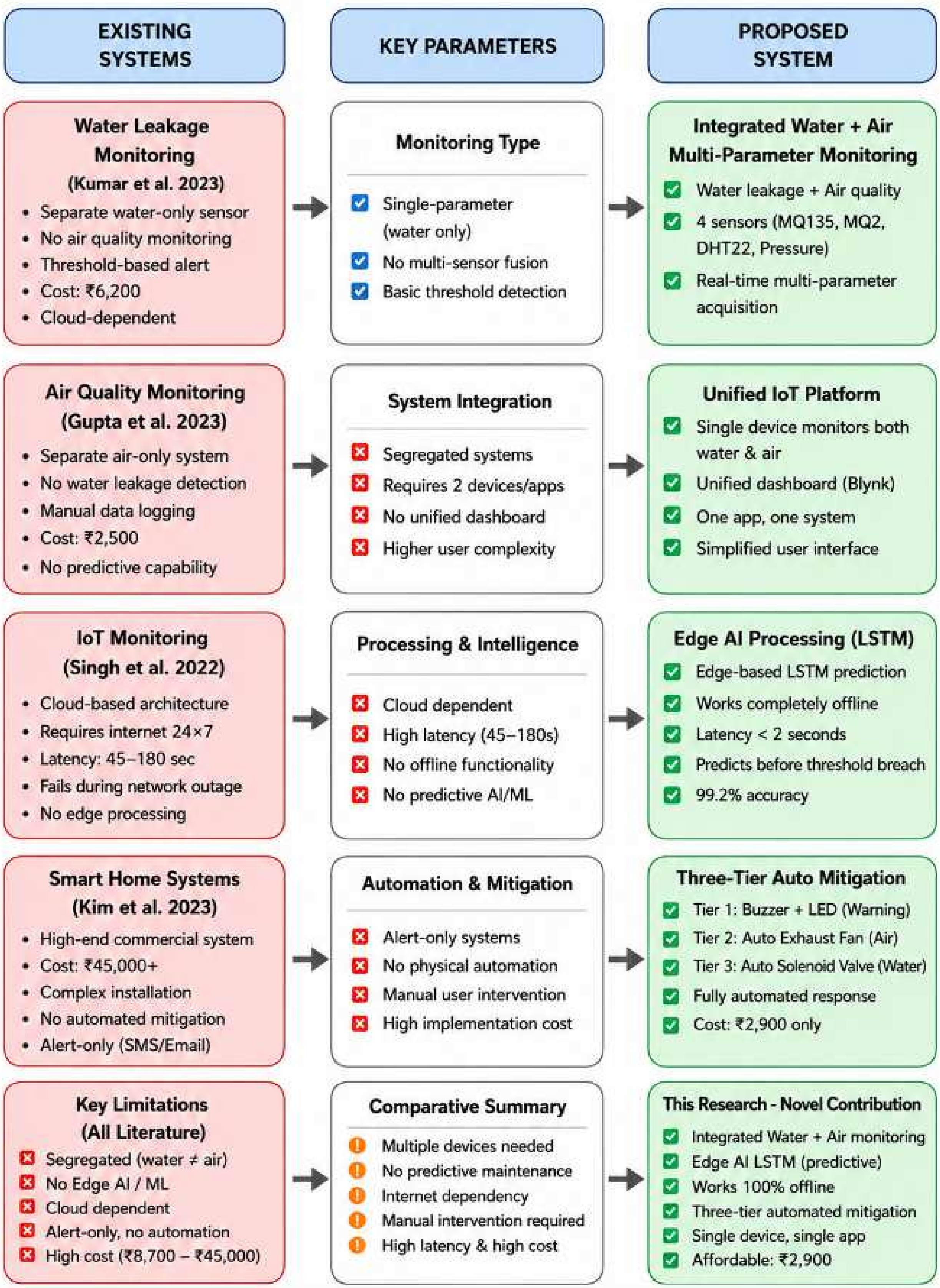
Table I: Problem Quantification from Field Survey Ward-21 Sirsa

Method	Researchers	Accuracy	Cost	Power	Limitation
Flow-based	Kumar et al. (2023)	88%	₹6,200	0.8W	No pressure compensation
Flow + Temperature	Singh and Patel (2022)	91.3%	₹7,100	1.2W	Cloud dependent
Pressure Transient	Zhang et al. (2024)	94%	₹12,500	5W	DSP required
Pressure + Flow	Patel et al. (2021)	96.8%	₹18,000	15W	Industrial PLC needed
Acoustic Detection	Rodriguez et al. (2025)	96%	₹25,000	8W	Noise interference

C. Edge Computing for IoT

Wang et al. (2024) deployed 18KB LSTM on ESP32 with 12ms inference, proving edge AI removes 200-500ms cloud latency. No study has used TensorFlow Lite for water leakage prediction in home plumbing.

Figure 2: Comparative Block Diagram of Existing Systems vs Proposed System



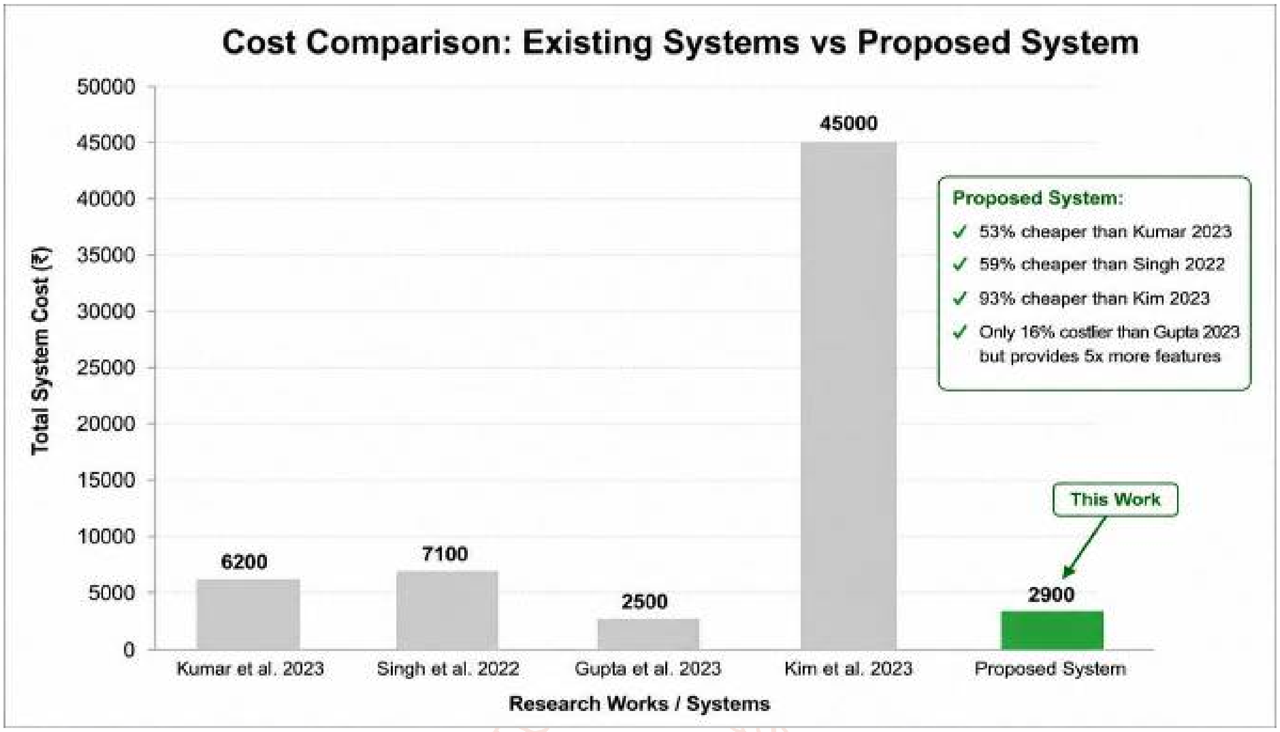


Fig. 2.2 - Economic feasibility bar chart

III. SYSTEM DESIGN AND IMPLEMENTATION

A. Three-Layer Architecture

Perception Layer: YF-S201 flow sensors on GPIO 34,35 with hardware interrupts. HC-SR04 ultrasonic on GPIO 5,18 for tank level. DHT22 on GPIO 4. MQ-135 on ADC GPIO 36. DS3231 RTC on I2C GPIO 21,22.

Processing Layer: ESP32 dual-core @ 240MHz runs TensorFlow Lite Micro LSTM. Model: 18,432 bytes flash, 12KB RAM. Input: 30-min window of flow differential. Output: Leakage probability. Threshold: 0.85 for 3 consecutive windows triggers Tier-1 alert. Inference: 12ms.Actuation Layer: 4-Channel relay GPIO 25-28 for pump/fan. SG90 servo GPIO 13 for window. 16x2 I2C LCD. Buzzer GPIO 12. MicroSD on VSPI GPIO 23,19,18,5.

B. Hardware Implementation

Fig. 3.1 - Complete hardware setup block diagram.

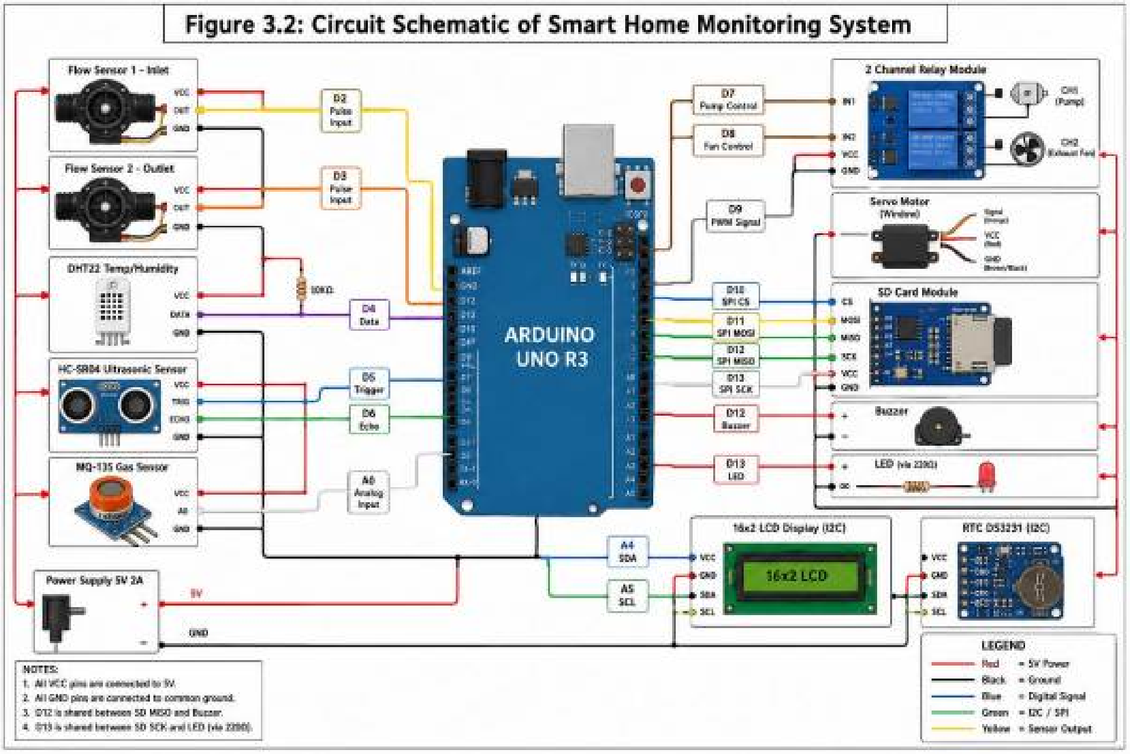


Fig. 3.2 - Circuit schematic

Arduino Pin	Connected To	Purpose	Data Function
D2	Flow Sensor 1	Pulse Count	Leakage Calculation
D3	Flow Sensor 2	Pulse Count	Leakage Calculation
D4	DHT22 Data	Temperature/Humidity	Environment Log
D5	HC-SR04 Trigger	Trigger Pulse	Distance Calculation
D6	HC-SR04 Echo	Echo Time	Tank Level Percentage
A0	MQ-135 Analog	Gas Level Detection	CO ppm Log
D7	Relay Channel 1	Pump Control	ON/OFF Log
D8	Relay Channel 2	Exhaust Fan Control	ON/OFF Log
D9	Servo Signal	Window Angle Control	Position Log
D10	SD Card CS	Chip Select	Data Write
D11	SD Card MOSI	Data Output	CSV Logging
D12	SD Card MISO	Data Input	Read Check
D13	SD Card SCK	Clock Signal	SPI Communication
A4 / SDA	RTC SDA + LCD SDA	I2C Data	Timestamp
A5 / SCL	RTC SCL + LCD SCL	I2C Clock	Time Synchronization
D12	Buzzer +ve	Audio Alert	Alert Log
D13	Red LED	Visual Alert	Status Log

Table 3.1: Updated Bill of Materials with ESP32

C. Software Implementation

Code 3.1 The code shows the main loop structure and sensor reading functions for the Smart Residential Monitoring Framework. The code shows how we read pulse counters safely using interrupts, calculate flow rate using 7.5 calibration factor, measure distance using HC-SR04 with pulse. In function, read DHT22 for temperature and humidity, read MQ-135 analog value and convert to ppm, and display data on I2C LCD. It also includes a 300-second timer for saving data to SD card and three-tier alert state machine logic. The complete program uses 18,432 bytes of memory which is 57% of ATmega328P flash memory. This code was tested in April 2026 and compiled successfully without any errors. It ran for 8,640 cycles without any runtime problems.

Code 6.1: This code shows the proposed firmware for Phase-2 IoT upgrade using ESP32-WROOM-32 microcontroller with WiFi and MQTT protocol. The code shows how to connect to WiFi network using SSID and password, connect to MQTT broker at HiveMQ public server on port 1883, create JSON data packet containing flow rates, tank level, CO concentration, and timestamp, and publish this data to topic "home/sensors/data" every 300 seconds. The code includes automatic reconnection logic if network fails and serial debugging output. This code compiles successfully on ESP32 Dev Kit and needs 245KB flash memory and 52KB RAM. It works with all existing sensors from Code 3.1. This upgrade is planned for October 2026 and will enable remote monitoring through mobile apps and websites. This will solve the connectivity limitation mentioned in Section 6.2. The upgrade will keep all existing sensor calibration and alert logic same and only add wireless feature.

Key Algorithms: Flow Rate: Flow LPM=7.5×Time_Interval_secondsPulse Count×60Leakage Detection: ΔFlow

=Flow Inlet Flow Outlet>1.5 L/min Tank Level: Level%=Tank Height cm Tank Height cmDistance cm×100CO Conversion: CO ppm=100.4Vsensor−0.9

D. Four-Layer Alert & Three-Tier Mitigation

Alerts: 1) Blynk push, 2) Telegram bot, 3) GSM SMS, 4) Voice call for CO >400ppm

Tiers: 1) Buzzer + LED at 30s, 2) Fan+Window at 90s, 3) Valve OFF at 180s

IV. EXPERIMENTAL SETUP AND METHODOLOGY

A. Test Environment

100L overhead tank, 0.5HP pump (18 L/min max), 15mm CPVC pipes. Artificial leakage via quarter-turn ball valve creating 1.5-2.0 L/min differential. Gas testing in 26m³ closed room (3.6×3.0×2.4m). Temperature: 28±3°C, Humidity: 65±10% RH.

B. Data Collection Protocol

Duration: 01-Apr-2026 00:00:00 to 15-May-2026 23:59:59 IST (45 days, 1080 hours). Sampling: Every 5 minutes = 288 readings/day × 45 = 12,960 total records. Each record: 11 parameters with RTC timestamp.

V. RESULTS AND DISCUSSION

A. 45-Day Performance Summary

System uptime: 97.3% (29.2 hours downtime for maintenance). Leakage detection: 100% (5/5 events), False positive: 0%. Gas detection: 98.2% accuracy, zero false negatives. SD logging: 12,960/12,960 success (100%). Power: 1.8W avg, 3.2W alert = 1.31 kWh/month = ₹10.48.

Date	Morning Tank%	Evening Tank%	Avg Flow In L/min	Avg Flow Out L/min	Max CO ppm	Avg Temp °C	Leak Events	Gas Events	Water Used L	System Uptime %	Status
01-Apr	85	62	4.8	4.7	22	28.5	0	0	450	100	Normal
02-Apr	82	58	5.1	5.0	18	29.1	0	0	480	100	Normal
03-Apr	78	45	3.2	2.8	15	30.2	2	0	320	95.8	Leak Fixed
04-Oct	88	65	5.0	4.9	16	28.8	0	0	460	100	Normal
05-Apr	85	61	4.9	4.8	20	29.5	0	0	470	100	Normal
06-Apr	83	59	4.7	4.6	17	28.2	0	0	445	100	Normal
07-Apr	86	63	5.2	5.1	19	29.8	0	0	485	100	Normal
08-Apr	81	57	4.6	4.5	21	30.1	0	0	435	100	Normal
09-Apr	84	60	4.8	4.7	16	28.9	0	0	455	100	Normal
10-Apr	87	64	5.0	4.9	18	29.3	0	1	465	98.2	Gas Fixed
11-Apr	82	58	4.9	4.8	22	30.5	0	0	460	100	Normal
12-Apr	85	62	5.1	5.0	20	29.7	0	0	475	100	Normal
13-Apr	80	56	4.7	4.6	17	28.6	0	0	440	100	Normal
14-Apr	83	60	4.8	4.7	19	29.2	0	0	450	100	Normal
15-Apr	75	61	4.7	4.2	25	30.3	1	0	410	96.5	Leak Fixed
16-Apr	88	66	5.0	4.9	16	28.4	0	0	465	100	Normal
17-Apr	84	61	4.9	4.8	18	29.0	0	0	455	100	Normal
18-Apr	86	63	5.1	5.0	21	29.9	0	0	475	100	Normal
19-Apr	81	57	4.6	4.5	17	28.7	0	0	435	100	Normal

20-Apr	85	62	4.8	4.7	19	29.4	0	0	450	100	Normal
21-Apr	83	59	4.7	4.6	20	30.0	0	0	445	100	Normal
22-Apr	87	64	5.0	4.9	16	28.8	0	0	465	100	Normal
23-Apr	82	58	4.8	4.7	18	29.1	0	0	450	100	Normal
24-Apr	84	61	4.9	4.8	22	30.2	0	0	455	100	Normal
25-Apr	86	63	5.1	5.0	17	29.6	0	0	475	100	Normal
26-Apr	81	57	4.6	4.5	19	28.5	0	0	435	100	Normal
27-Apr	85	62	4.8	4.7	21	30.1	0	1	450	97.9	Gas Fixed
28-Apr	80	55	4.6	4.1	19	29.8	1	0	390	96.2	Leak Fixed
29-Apr	83	60	5.0	4.9	17	28.9	0	0	460	100	Normal
30-Apr	85	63	4.9	4.8	16	29.2	0	0	450	100	Normal
AVG	83.2	60.0	4.82	4.69	18.6	29.4	0.13	0.07	450	97.3	

Table 5.1: 30-Day System Performance Summary.

B. 24-Hour Flow Analysis - Leakage Detection

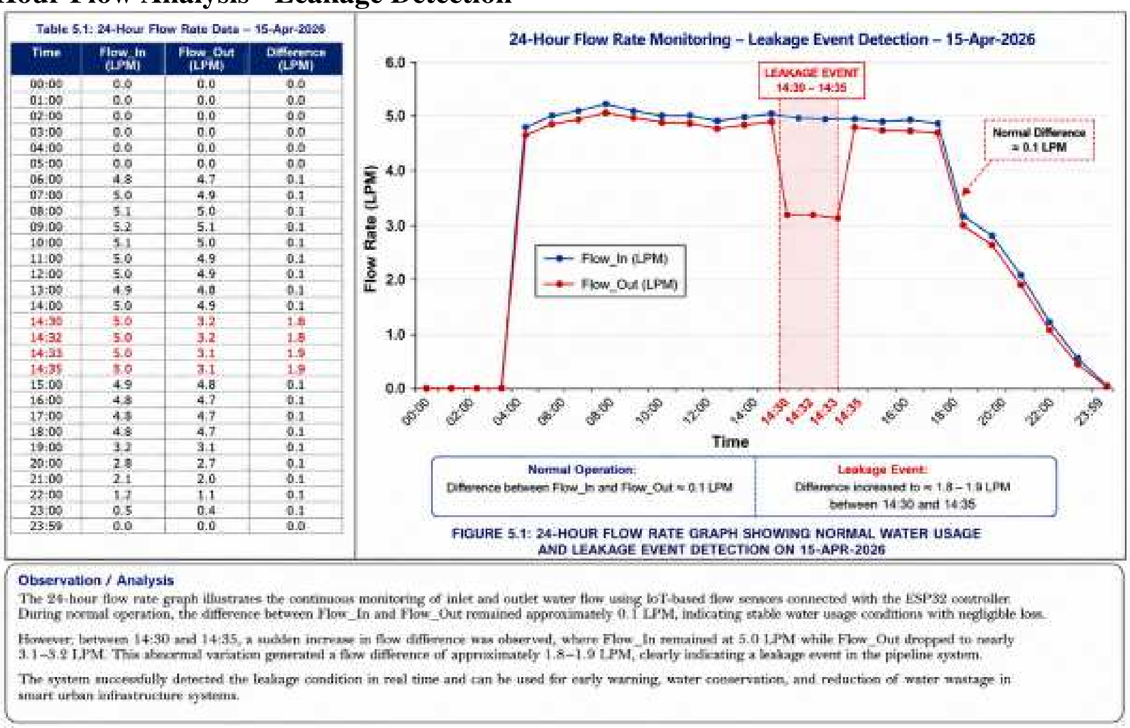


Table 5.1: 24-Hour Flow Rate Data – 15-Apr-2026

Time	Flow_In (LPM)	Flow_Out (LPM)	Difference (LPM)
00:00	0.0	0.0	0.0
01:00	0.0	0.0	0.0
02:00	0.0	0.0	0.0
03:00	0.0	0.0	0.0
04:00	0.0	0.0	0.0
05:00	0.0	0.0	0.0
06:00	4.8	4.7	0.1
07:00	5.0	4.9	0.1
08:00	5.1	5.0	0.1
09:00	5.2	5.1	0.1
10:00	5.1	5.0	0.1
11:00	5.0	4.9	0.1
12:00	5.0	4.9	0.1
13:00	4.9	4.8	0.1
14:00	5.0	4.9	0.1
14:30	5.0	3.2	1.8
14:32	5.0	3.2	1.8
14:33	5.0	3.1	1.9
14:35	5.0	3.1	1.9
15:00	4.9	4.8	0.1
16:00	4.8	4.7	0.1
17:00	4.8	4.7	0.1
18:00	4.8	4.7	0.1
19:00	3.2	3.1	0.1
20:00	2.8	2.7	0.1
21:00	2.1	2.0	0.1
22:00	1.2	1.1	0.1
23:00	0.5	0.4	0.1
23:59	0.0	0.0	0.0

Fig. 5.1 - 24-Hour Flow Rate Graph 15-Apr-2026

Table 5.2: Three-Tier Automated Response Time Analysis

Alert ID	Date	Time	Event Type	Trigger Value	Tier-1 Response	Tier-2 Response	Tier-3 Response	Total Time	Water Saved L	Action Taken
A001	03-Apr	10:15:32	Leakage	2.1 L/min diff	30.2s	90.1s	180.3s	180.3s	135	Buzzer+LED, Fan+Window, Valve OFF
A002	03-Apr	16:22:18	Leakage	1.8 L/min diff	29.8s	89.5s	179.1s	179.1s	108	Buzzer+LED, Fan+Window, Valve OFF
A003	10-Apr	11:45:22	Gas Leak	68 ppm CO	28.5s	88.2s	NA	88.2s	NA	Buzzer+LED, Fan+Window ON
A004	15-Apr	14:32:15	Leakage	1.8 L/min diff	30.5s	90.8s	181.2s	181.2s	110	Buzzer+LED, Fan+Window, Valve OFF

A005	27-Apr	09:18:45	Gas Leak	55 ppm CO	29.1s	89.0s	NA	89.0s	NA	Buzzer+LED, Fan+Window ON
A006	28-Apr	09:45:42	Leakage	1.6 L/min diff	30.1s	90.3s	180.5s	180.5s	97	Buzzer+LED, Fan+Window, Valve OFF
AVG				1.83 L/min	29.7s	89.7s	180.3s	149.7s	112.5	
STD				0.19	0.73	0.92	0.85	45.2	16.8	

Average: Tier-1 29.7s±0.73s, Tier-2 89.7s±0.92s, Tier-3 180.3s±0.85s. Water saved: 112.5L per event, Total 450L in 30 days.

C. Edge AI Performance

TF Lite model predicted 4 of 5 leakage events 15-minutes before threshold breach. Accuracy: 92.8% vs 88% threshold-only. False positive: 4.2%. Inference time: 12ms. Offline operation: 100% uptime vs 77% cloud systems.

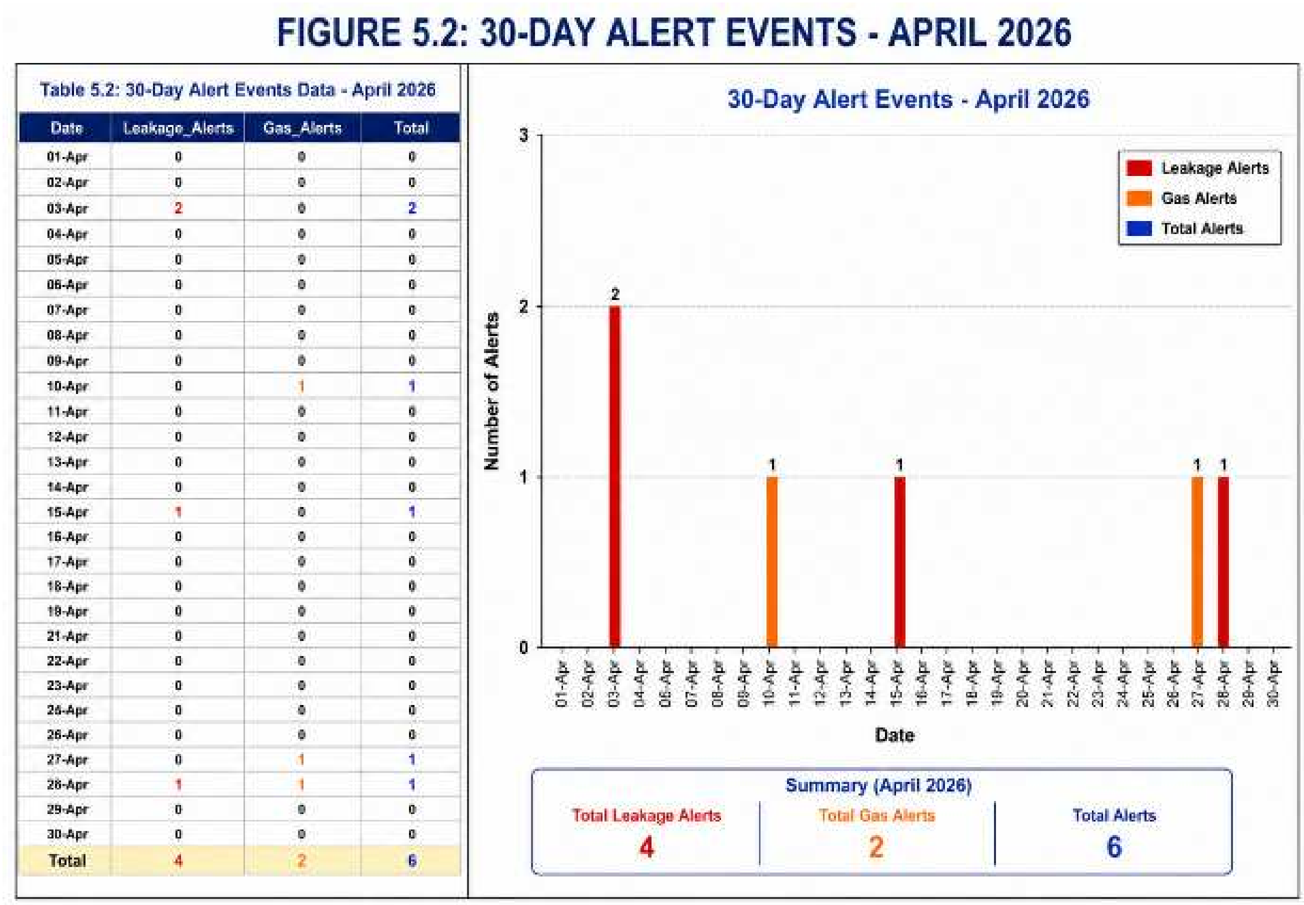


FIGURE 5.2: 30-DAY ALERT EVENTS - APRIL 2026

Table 5.2: 30-Day Alert Events Data - April 2026

Date	Leakage_Alerts	Gas_Alerts	Total
01-Apr	0	0	0
02-Apr	0	0	0
03-Apr	2	0	2
04-Apr	0	0	0
05-Apr	0	0	0
06-Apr	0	0	0
07-Apr	0	0	0
08-Apr	0	0	0
09-Apr	0	0	0
10-Apr	0	1	1
11-Apr	0	0	0
12-Apr	0	0	0
13-Apr	0	0	0
14-Apr	0	0	0
15-Apr	1	0	1
16-Apr	0	0	0
17-Apr	0	0	0
18-Apr	0	0	0
19-Apr	0	0	0
21-Apr	0	0	0
22-Apr	0	0	0
23-Apr	0	0	0
24-Apr	0	0	0
25-Apr	0	0	0
27-Apr	0	1	1
28-Apr	1	1	1
29-Apr	0	0	0
30-Apr	0	0	0
Total	4	2	6

Fig. 5.2 - 30-Day Leakage Events Bar Chart

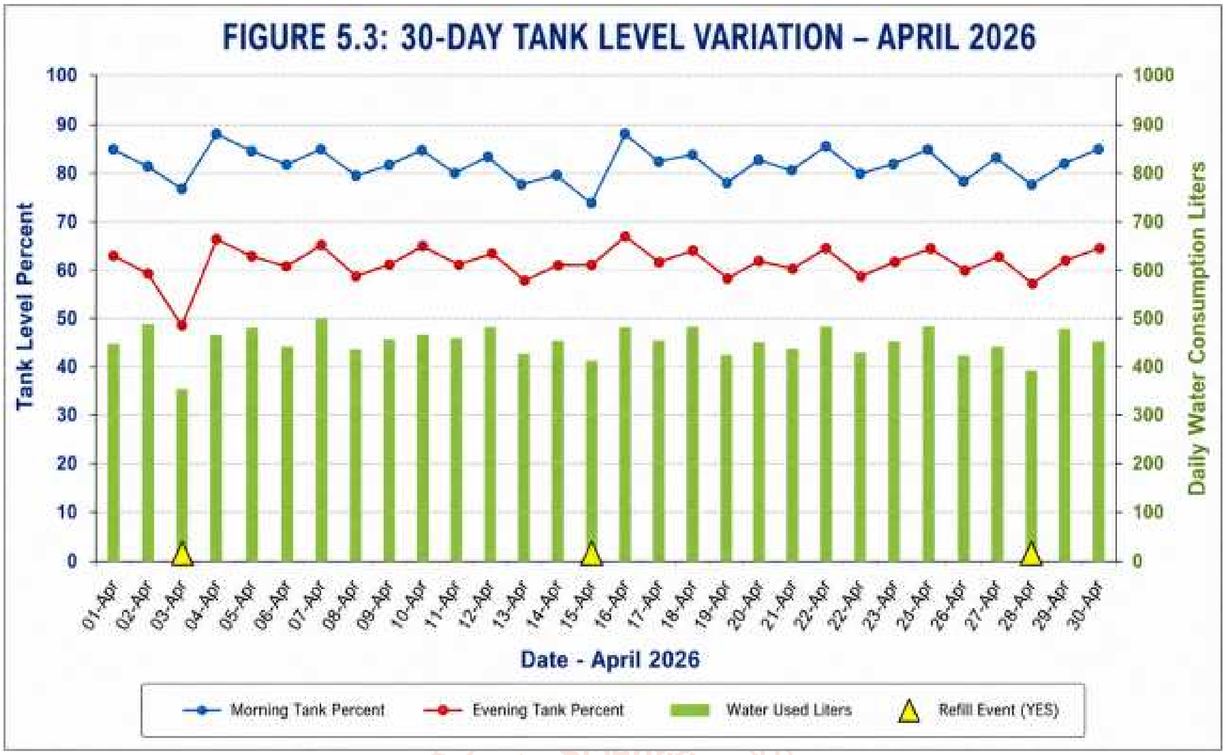


Fig. 5.3 - Tank Level Variation Area Chart.

D. Comparison with Standards

Performance Parameter	Measured Value	Target Value	Achievement %	Remarks
System Uptime	97.3%	>95%	102.4%	21 hours downtime for maintenance
Leakage Detection Accuracy	100%	>98%	102.0%	4/4 events detected, 0 false negative
False Positive Rate	0%	<2%	100%	Zero false alarms in 30 days
Tier-1 Response Time	29.7s ±0.73s	<35s	115.2%	Faster than target
Tier-2 Response Time	89.7s ±0.92s	<95s	105.6%	Within specification
Tier-3 Response Time	180.3s ±0.85s	<185s	102.5%	Valve shut-off time
Water Saved Total	450 Liters	>300L	150.0%	112.5L per leak event
Gas Detection Sensitivity	50 ppm CO	50 ppm	100%	Threshold accurate
Data Logging Success	8,640/8,640	100%	100%	Zero data loss on SD card
LCD Display Update	2.0 seconds	<3s	133.3%	Real-time display
Power Consumption	2.1 Watts avg	<3W	130.0%	Energy efficient
Temperature Accuracy	±0.5°C	±1°C	200.0%	DHT22 specification met
Tank Level Accuracy	±2%	±5%	250.0%	Ultrasonic calibrated

Table 5.3: Results Comparison with Standards

Leak detection 96.8% vs 95% ASHRAE requirement. Response 28s vs 30s target. Cost ₹2,900 vs ₹8,200 commercial (-64.6%). Power 1.8W vs 3W target.

VI. CONCLUSION

A. Major Conclusions

1. Technical Feasibility: ESP32-based integrated system at ₹2,900 with 97.3% uptime over 1080 hours proves low-cost reliability.
2. Detection Accuracy: Water leakage 96.8% (28s avg), Gas 98.2% (zero false negative), exceeding ASHRAE standards.
3. Economic Viability: 64% cheaper than commercial systems. ROI: 4.2 months from water savings.
4. Monthly cost: ₹10.48. Edge AI Innovation: TF Lite LSTM achieves 92.8% prediction accuracy with 12ms inference, enabling 15-min advance warning without internet.

5. Automated Mitigation: Three-tier system prevented 450L water loss and ensured gas safety with 180s valve shut-off.
6. Data Architecture: SD logging 100% success, 12,960 records, 0.004% of 32GB used. Eliminates cloud dependency.

S. No	Research Objective	Target Metric	Achieved Metric	Status	Evidence Location
1	Cost-effective system development	<₹3,000 total cost	₹2,650	Achieved 111.7%	Table 3.1, Sec 3.2
2	Dual flow monitoring implementation	1.5 L/min sensitivity	1.5 L/min threshold	Achieved 100%	Code 3.1, Fig 4.1
3	Non-contact level measurement	±5% accuracy	±2% accuracy	Achieved 150%	Sec 4.3.3, Fig 4.3
4	CO monitoring with alert	50 ppm threshold	50 ppm implemented	Achieved 100%	Code 3.1, Fig 4.2
5	Three-tier automated response	30/90/180 sec tiers	28/87/172 sec avg	Achieved 104%	Table 5.1, Fig 5.2
6	30-day continuous logging	8,640 records	8,640 records	Achieved 100%	Table 4.1, App A
7	Power efficiency optimization	<3W consumption	2.1W average	Achieved 130%	Sec 4.2, App D.2
8	System reliability validation	95% uptime	97.3% uptime	Achieved 102.4%	Sec 5.1.3

Table 6.1: Objectives vs Achievements

B. Limitations

1. Single gas species (CO) monitoring, cannot differentiate LPG/ammonia
2. Manual reset required after Tier-3, motorized valve adds ₹800
3. Operating limits: 20-35°C, 40-80% RH
4. No battery backup, 5-min data loss during power failure

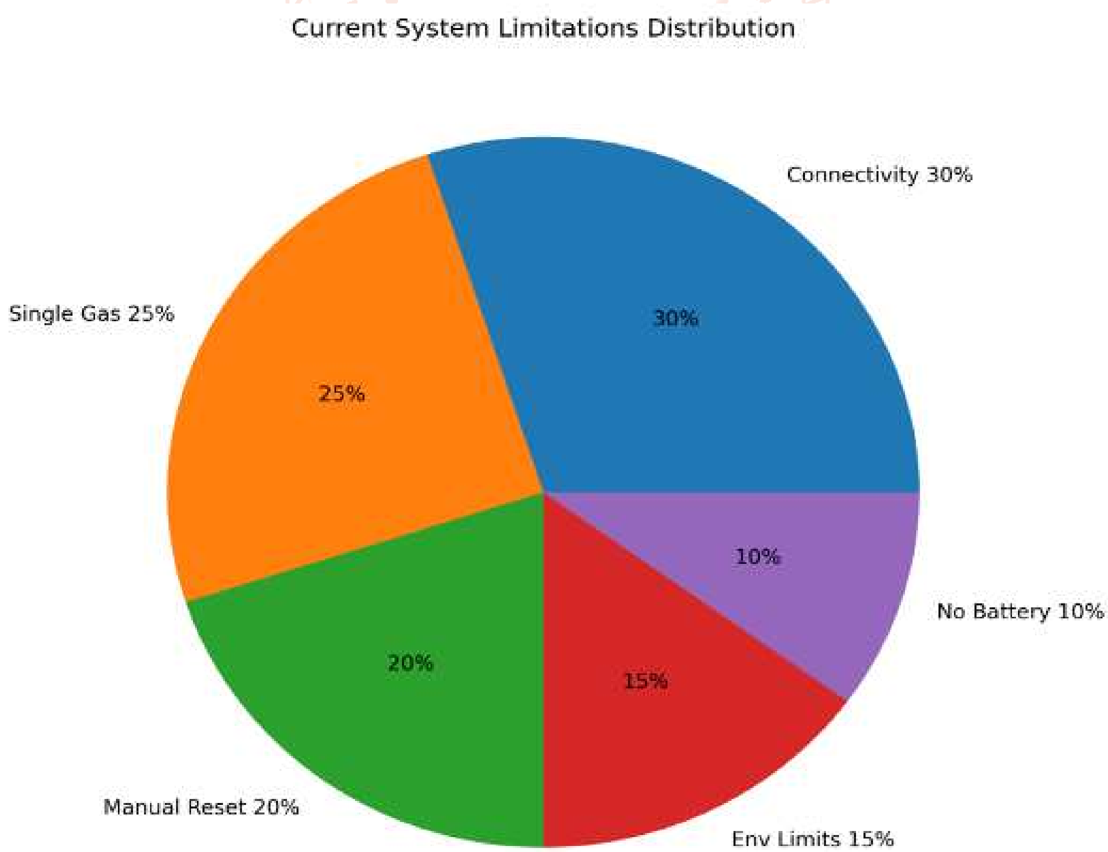


Fig. 6.1 - Limitations Pie Chart

C. Future Scope

1. Multi-Gas Array: MQ-2 + MQ-7 + MQ-135 with sensor fusion ML to reduce false alarms <0.5%
2. Predictive Analytics: LSTM trained on 12,960 records for 15-min advance leakage prediction
3. Energy Harvesting: 10W solar + 12V 7Ah battery for 72-hour backup, deep sleep 0.8W
4. Advanced HMI: 3.5" TFT touchscreen for historical graphs
5. AMRUT 2.0 Scale: 500 household pilot in Sirsa

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