IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

"Behavioural Analysis of Water Consumption Using IoT-Based Smart Retrofit Meter"

RameGowda M,
Dept of Electronics and Communication
SJC Institute of Technology Chickballapur,Karnataka,India
Naveen A
Dept of Electronics and Communication
SJC Institute of Technology Chickballapur,Karnataka,India

ABSTRACT— ***An IoT-enabled smart retrofit meter-based framework for real-time behavioral analysis of water consumption is presented in this paper***. This paper explores the integration of IoT-based smart retrofit meters with deep learning algorithms for analyzing water consumption in educational campuses. The system captures meter images, processes them locally using ResNet-18 for digit recognition, and refines this data through a Hamming distance-based approach before cloud transmission for real-time analysis. The study focuses on water usage in both student hostels and faculty quarters within an Intermittent Water Supply (IWS) system, capturing variations influenced by factors like academic schedules, holidays, and lifestyle differences. Results demonstrate that student hostels exhibit more dynamic usage patterns, while faculty quarters show relatively consistent demand. These findings underscore the potential for scalable, data-driven water management solutions tailored to diverse residential settings.

Keywords: Deep learning, IoT, ResNet-18, Hamming distance, Real-time analysis, Digit detection algorithm.

INTRODUCTION

Water is an indispensable resource, fundamental to human existence and societal functioning. Ensuring reliable and equitable access to clean water through efficient distribution systems is a global priority, crucial for public health and resource management. Traditional water distribution often relies on analog meters, lacking the capability for real-time monitoring and detailed consumption analysis. Modern solutions often involve smart meters, especially within Continuous Water Supply (CWS) systems common in developed nations, which leverage Advanced Metering Infrastructure (AMI) for high-frequency data collection.

However, many regions, particularly in developing countries, operate under Intermittent Water Supply (IWS) systems. These systems deliver water according to schedule rather than continuously, often due to limited resources or infrastructure constraints. IWS poses unique challenges: it necessitates additional consumer infrastructure (like storage tanks) and makes implementing conventional AMI and smart metering financially and operationally difficult. Yet, understanding detailed consumption patterns is arguably even more critical in IWS to manage scarce resources effectively, ensure adequate supply during scheduled periods, and minimize wastage. The Internet of Things (IoT) presents a promising avenue to bridge this gap, enabling the development of cost-effective "smart" solutions even for legacy infrastructure.

The conventional approach to water metering involves manual reading of analog meters, which is labor-intensive, prone to errors, and provides only low-frequency data (e.g., monthly readings). This limits any detailed analysis of consumption behavior.

In advanced CWS scenarios, existing smart systems typically involve replacing traditional meters with sophisticated digital smart meters integrated into an AMI. This infrastructure supports two-way communication and provides high-resolution data, facilitating leak detection, demand forecasting, and efficient network management. However, the high cost of meter replacement and the operational complexities of AMI make this make this approach less feasible for widespread adoption in IWS environments.

1. PROBLEM STATEMENT

Effective water management in Intermittent Water Supply (IWS) systems is challenging due to the lack of high-resolution data, high costs of smart meter deployment, and data quality issues in retrofit solutions. Analog meters, common in IWS, often suffer from errors caused by environmental factors and installation inconsistencies. Understanding user-specific consumption patterns, influenced by factors like academic schedules and holidays, requires a cost-effective, reliable approach for accurate, high-frequency data collection.

PROPOSED SYSTEM ARCHITECTURE

1. System Overview

The proposed system is an end-to-end IoT-based framework designed to retrofit existing analog water meters for smart water consumption monitoring. It utilizes a low-cost, Raspberry Pi-based device with a PiCamera, LED ring, and 3D-printed housing for precise dial imaging. The on-device intelligence captures meter readings at regular intervals, processes the images to isolate the Region of Interest (RoI), and employs a ResNet-18 deep learning model for digit recognition. To enhance accuracy, a Hamming distance-based refinement algorithm corrects potential errors by comparing current and past readings within plausible ranges. This system effectively converts analog meters into smart devices, offering a cost-efficient alternative for high-frequency data collection in Intermittent Water Supply (IWS) systems, enabling detailed consumption pattern analysis across diverse user groups.

2. System Architecture

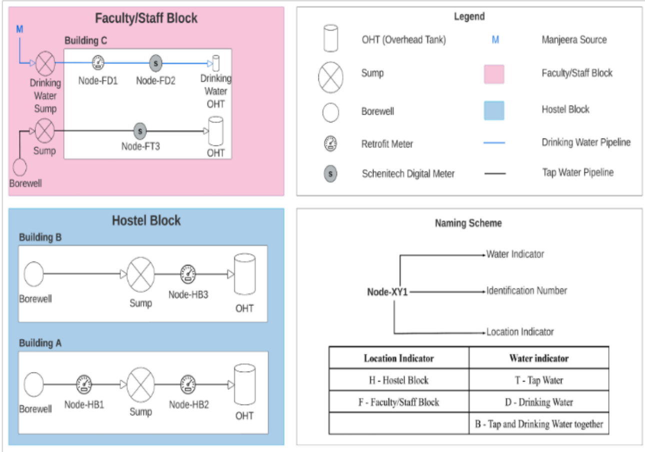

Fig1: Representation of Water Distribution Model.

As seen in the Fig1, the system includes the following elements

1) Faculty/Staff Block (Pink Region):
   - Buildings and Nodes:
     - Node-FD1 and Node-FD2 are installed in Building C, handling the drinking water supply from the sump to the Overhead Tank (OHT).
     - Node-FT3 is responsible for tap water supply, also connected to an OHT, providing detailed consumption data for faculty and staff.
   - Meter Setup:
     - Node-FD1 is a smart retrofit meter, while Node-FD2 is a Shenitech Digital Meter, allowing cross-verification of meter readings for enhanced accuracy.
   - Water Sources:
     - Water is sourced from a borewell, stored in a sump, and then pumped to the OHT before distribution.
2) Hostel Block (Blue Region):
   - Buildings and Nodes:
     - Node-HB1, positioned between the borewell and sump, and Node-HB2, located between the sump and overhead tank (OHT), are installed in Building A.
     - Building B has Node-HB3, monitoring water supply from sump to OHT.
3) Legend and Naming Scheme:
   - The legend clarifies the different water sources and pipeline types, including

drinking water, tap water, and borewell connections.

- The naming scheme (Node-XY1) indicates the block type (H for Hostel, F for Faculty), water indicator (B for both tap and drinking, D for drinking, T for tap), and a unique node identifier.

Key Features of the Proposed System

Hardware Implementation

The hardware setup for this IoT-based water monitoring system relies on a cost-effective, custom-designed retrofit module. At its core, the system uses a Raspberry Pi 3B+ microcontroller for processing, paired with a PiCamera for high-resolution image capture of analog water meter dials. To ensure consistent lighting and clear image quality, the device includes an LED ring that minimizes shadows and reflections, crucial for accurate digit recognition. The entire assembly is encased in a 3D-printed enclosure, providing durability and precise alignment over the meter dial, facilitating straightforward installation.

Power reliability is a critical consideration, so the system supports both AC and battery power to prevent data loss during outages. Additionally, the Raspberry Pi handles the real-time control of the camera, triggering image captures at fixed intervals, typically every minute, to provide high-frequency consumption data. This setup effectively transforms legacy analog meters into smart devices capable of detailed, continuous monitoring without the need for costly full replacements.

To enhance the robustness of the design, the retrofit device incorporates hardware features that optimize data quality. This includes precise positioning of the camera for accurate digit framing and a stable mounting system that reduces the risk of misalignment.

Software Implementation

The software side of this system integrates several critical components for efficient data processing and transmission. Initially, the captured images are preprocessed to isolate the Region of Interest (RoI) containing the analog meter digits. This step involves perspective correction using OpenCV, ensuring that the extracted digit areas are free from distortion and well-aligned for subsequent analysis.

Once the RoI is extracted, the digits are segmented and fed into a deep learning-based recognition model. The system uses a ResNet-18 convolutional neural network (CNN) with transfer learning, chosen for its balance of accuracy and computational efficiency. This model, pre-trained on the extensive ImageNet dataset and fine-tuned for the specific task of digit recognition, provides fast, reliable reading outputs directly on the edge device, reducing the need for constant cloud communication.

I. HARDWARE DESCRIPTION

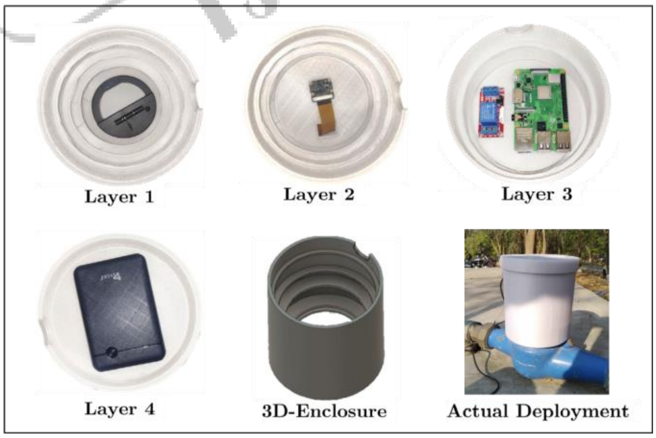

Fig 2: The retrofit model.

1. Physical Enclosure and Mounting Layer:

The physical structure of the retrofit system uses a custom-designed, 3D-printed enclosure that securely houses key electronic components like the Raspberry Pi, PiCamera, and LED ring. This enclosure is tailored to fit analog water meters precisely, ensuring stable placement for accurate image capture while providing protection against dust, moisture, and physical impacts. It maintains a clear view of the meter dial, ensuring consistent data collection even in challenging environments.

2. A Image Capture and Illumination Layer:

This layer comprises the PiCamera for capturing high-resolution images of the meter dial and an LED ring to provide uniform illumination. This lighting setup is critical for minimizing shadows and glare, ensuring clear digit extraction regardless of ambient light conditions. The PiCamera was selected for its compatibility with the Raspberry Pi, cost-effectiveness, and compact design, making it ideal for this application.

3. Edge Processing and Digit Recognition Layer:

The edge processing unit, built around the Raspberry Pi 3B+, handles image processing and digit recognition locally. It isolates the Region of Interest (RoI) from the captured images using perspective correction and contour detection algorithms. This processed data is then fed into a ResNet-18 model, fine-tuned for high-accuracy digit recognition using transfer learning, allowing for rapid and reliable number extraction.

4. Data Refinement and Error Correction Layer:

This layer addresses potential image errors using a Hamming distance-based algorithm. It compares the current reading with the previous validated reading, correcting minor digit recognition errors that can arise due to noise or slight misalignments. This approach significantly improves data reliability by reducing false positives and the need for manual corrections.

5. Data Transmission and Cloud Integration Layer:

After local refinement, meter readings are transmitted to a cloud server for long-term storage and analysis. This layer manages secure, real-time data transmission over Wi-Fi, supporting continuous monitoring and scalable deployment. The cloud component also facilitates advanced analytics, including consumption forecasting and anomaly detection, making the system adaptable to various infrastructure sizes.

6. User Interface and Data Visualization Layer:

A user interface provides real-time data visualization, offering insights through intuitive dashboards. These dashboards present daily, weekly, and monthly usage patterns, helping facility managers optimize resource distribution and quickly identify anomalies.

II. SOFTWARE DESCRIPTION

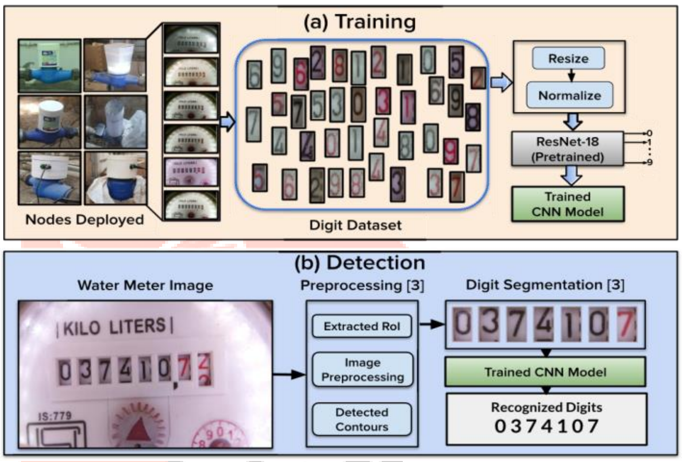

Fig 3. CNN Model and ResNet-18 Training and Detection Model

1. Data Capturing from Meter

The software layer integrates data capture, preprocessing, and machine learning for accurate digit detection. Key steps include:

- **Data Acquisition:** Collecting raw signals through sensors and converting them into digital data using ADCs.
- **Preprocessing:** Filtering and normalizing the data for consistency and accuracy, reducing noise and enhancing signal quality.
- **Feature Extraction:** Identifying key parameters like power factor, harmonic levels, and phase angles to create a robust dataset.
- **Real-Time Data Transmission:** Securely sending processed data to cloud servers for real-time analysis and long-term storage, supporting data-driven decision-making.

2. ResNet-18 Description

ResNet-18 is a convolutional neural network (CNN) architecture that features 18 layers designed to effectively handle the challenge of vanishing gradients in deep learning. It achieves this by incorporating residual connections, which allow the network to bypass certain layers, enabling smoother gradient flow during backpropagation and facilitating the training of deeper models. The architecture consists of:

- Initial Convolution Layer: A 7x7 convolution followed by batch normalization, a ReLU activation function, and a 3x3 max-pooling layer, forming the initial feature extraction stage.
- Residual Blocks: Four groups of residual blocks, each containing two convolutional layers. These blocks include identity connections that add the input of each block directly to its output, promoting stable gradient updates.
- Global Average Pooling: This layer reduces the spatial dimensions of the feature maps before classification, minimizing overfitting by averaging each feature map.
- Fully Connected Layer: A final layer that outputs the predicted class based on the extracted features, aligning the model for tasks like image classification.

III. RESULT AND DISCUSSION

The time series plot captures water volume data across different nodes over a one-month period, revealing distinct consumption trends. Dotted thick lines depict the raw data for each node, while the corresponding thin solid lines represent the best-fit linear trends. Notably, nodes associated with high-occupancy areas, like student hostels, exhibit steeper slopes, indicating higher water demand. This pattern aligns with the intensive water usage in student living spaces, which typically include facilities like dining areas and common washrooms. In contrast, nodes like Node-FD1, designated for drinking water supply, show a flatter trend, reflecting more stable but lower overall water consumption.

To complement this, the table outlining average water supply intervals to overhead tanks (OHT) provides insight into the periodic nature of the IWS (Intermittent Water Supply) system. For instance, Node-HB2, a critical supply point for student accommodations, reports an average refilling interval of around 18.8 hours. This frequency aligns closely with observed usage patterns, supporting efficient tank refilling and minimizing supply interruptions during peak demand periods.

Together, these insights highlight the importance of aligning water supply schedules with consumption patterns to optimize resource utilization. Understanding these dynamics is crucial for enhancing the reliability and efficiency of water distribution systems, particularly in environments where demand can fluctuate significantly due to varying occupancy rates and usage behaviors.

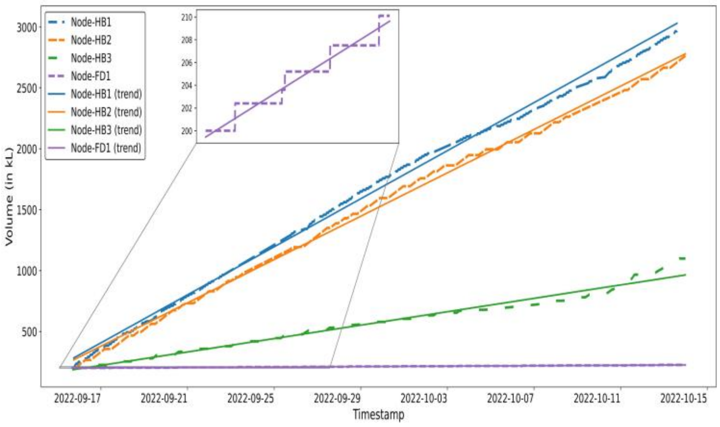

Fig 4. Time series plot for net water volume in kL.

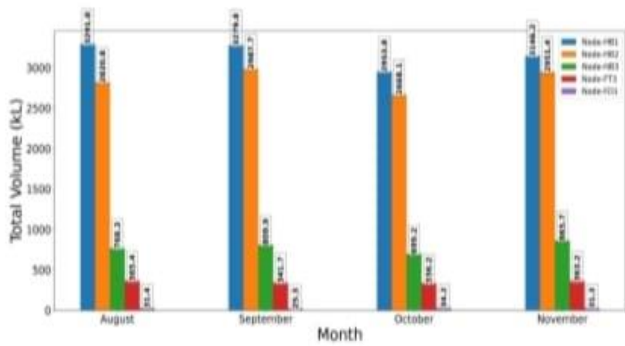

Fig 5. presenting the typical time intervals between consecutive water supplies.

IV. APPLICATIONS

1. Smart Metering for Water Management

The primary application demonstrated in this research is the use of IoT-based smart retrofit meters for monitoring water usage. These meters capture high-frequency data, providing a detailed view of consumption patterns in buildings like student hostels and faculty quarters. The system captures meter readings through digit recognition and transmits the data to a cloud server, enabling real-time analysis and historical trend assessment.

2. Behavioral Analysis of Consumption Patterns

The study highlights the ability to analyze water consumption behaviors using data from smart meters. By examining the water usage trends within different residential blocks, such as hostels with high occupancy and faculty quarters with more stable usage, the system provides insights into peak. This data can inform better resource allocation and infrastructure planning, reducing operational costs and preventing water shortages.

3. Data-Driven Infrastructure Optimization

Another critical application is the use of smart meters to optimize water distribution systems. By continuously monitoring water flow and usage, these meters can identify inefficiencies, detect leaks, and guide infrastructure upgrades. This data-centric method reduces water wastage and enhances the overall efficiency of the distribution system, making it especially beneficial for institutions with extensive residential facilities.

V. CONCLUSION

This project effectively implemented IoT-enabled smart retrofit meters for real-time water monitoring, significantly enhancing the accuracy and resolution of data collection compared to conventional IWS meters. By leveraging deep learning and advanced analytics, the system captured detailed consumption patterns, providing precise insights into usage trends across different zones. This approach not only reduced data transmission delays but also improved system responsiveness, supporting proactive maintenance and efficient resource management. The refined data enables better decision-making for infrastructure optimization, highlighting the potential for broader application in smart water distribution systems.

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