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IoT Water Management and Distribution System for Smart City using Artificial Intelligence

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Abstract

Year after year, the accessible percentage of the world's freshwater resources decreases. According to a World Economic Forum assessment, increased water consumption will result in catastrophic global shortages during the next two decades. The majority of water loss occurs during distribution in pipes during shipment. A water distribution system" using the Internet of Things (IoT) combining "cloud and fog computing" is presented for water distribution and underground pipeline health monitoring to remove the loss. Consumer needs must be assessed to design an effective IoT-based water supply system. As a result, a deep learning method known as Long short-term memory (LSTM) is suggested to estimate customer water consumption. An integrated IoT "Water Distribution Network (WDN)" is being created by employing hydraulic engineering and more accurate demand forecasts. The WDN design will minimize transport losses while maintaining water quality for users. This will result in the creation of smart systems for distributing water. Finally, the suggested algorithms' performance is analyzed and compared. The results demonstrate that the water distribution system with intelligence can effectively monitor the network.

Keywords: Water Distribution Network, Internet of Things, Long Short-Term Memory, Water Management, Smart City

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1. Introduction

Water is one of the most fundamental elements in the earth. Users today are always searching for methods to make their lives easier. Scrutinizing water quality is crucial to assuring the health of this planet and long-term survival [1]. Many infectious diseases are spread by water, and most of the adjacent freshwater supply is polluted by rubbish dumped by inhabitants and environmental disasters caused by industrial operations. Elevated tanks can hold potable water [2]. Microbial growth in elevated tanks and distribution networks, corrosion of piping materials, and failure to replace old piping are the primary reasons for water quality decline in residential buildings [3]. Continuous remote real-time water system quality metrics verification is required to avert catastrophic health effects [4].

Maximizing water use at the district or municipal level is a primary objective of self-sufficient and sustainable water management [5]. Methods of information, control, and monitoring use these resources. Water management minimizes leaks, maintains quality, improves the customer experience, and optimizes operations. IoT can contribute to long-term economic growth and enhance energy and water management by investing in citizens' well-being through IoT adoption [6]. Furthermore, water systems must be infused with technology to construct smart programs. Smart water distribution techniques can assist in enhancing the situation in multiple water techniques with poor infrastructure, uncertain supply and consumer satisfaction, or influential differences between bills and actual use. Adopting smart water distribution techniques has various advantages, including reducing financial losses and developing new business models that benefit rural and urban populations [7]. The advantages of IoT technique used in smart water distribution initiatives are now well understood. Thus, it can be used to better regulate the energy use and manage the resources. The primary goal of the research is to provide a new, dependable, and adaptive water quality monitoring system for real-time monitoring of remote water levels in IoT regions. Wireless sensor networks suggest an innovative architecture for collecting and transmitting information from diverse sources [8]. An IoT solution explicitly created for this network was subjected to extensive testing. The ultimate purpose of IoT networks is to enable water supply, distribution, and reservoir monitoring and management. This has been thoroughly tested and analyzed [9].

The importance of IoT devices is highlighted in this document. The water is highly required for as well as wasted in the household activities. The IoT-based tank level sensor device automatically turns on and off the motor and provides data for analysis to the cloud. Water levels may be monitored and controlled through an AI-based system, which can detect tank leaks and provide approximated measurements.

This research's primary contributions are:

- Water conservation, water management, and fault detection in smart water management Implementation of smart water distribution network
- Analyze the water usage and reduce the cost

The rest of the paper is structured as follows. Section 2 delves into the sensors, communication technologies, controllers, and application platforms employed in IoT-based water management systems. Section 3 highlights relevant work in the field of IoT-enabled water management systems. The architecture of the proposed water management IoT system is presented in Section 4. Section 5 presents conclusions.

2. Related Works

Lianxiu L et al. (2023) suggested a leak detection approach for urban water supply pipe networks using IoT technology and AI algorithms to address the issues of monitoring and identifying leaks in urban water supply pipe networks. First, low-cost, low-power terminal identification and gateway monitoring supplies should be designed for distant data transmission via Wi-Fi or cellular networks. Furthermore, the water supply pipe network leakage location model is built by employing remote pressure observing data to determine the precise position of the pipe system leakage. This research used the PSO and ALO optimization techniques to solve the water supply system of an industrial area in a specific city [10].

Rayed Al Ghamdi et al. (2022) presented an IoT-SWM (smart water management system) for constructions which do not have a steady water supply rather than storing water in massive tanks below. The GSM unit captures and transmits water use information from every resident dwelling to the cloud for analysis. The smart water management system is a hybrid model that detects leaks and monitors the consequent height difference to track tank water levels. Thus, the proposed approach is an outstanding alternative to Saudi Arabia's mechanical operating system [6].

Emmanuel Savio et al. (2021) created a water management and distribution system using the IoT and Data Analytics (DA), which will serve as the foundation for future deployment and a study on how data and IoT can be used to do this. This document offers a water management and distribution system using the Data Analytics (DA) and Internet of Things (IoT), which will aid in optimizing water distribution at the plot development level depending on user consumption. The proposed method not only minimizes water waste but also aids in the storage of usage data for macro-urban planning and analysis [11].

Alexandru Predescu et al. (2020) suggested a machine-learning (ML) framework for monitoring and controlling smart water networks. Automated test situations and learning approaches are suggested and aimed to forecast the network configuration of modern implementations of multi-model control monitors and improve their flexibility to changing operating conditions. Smart water meters enable sophisticated processing and components of smart water monitoring by supplying push-based and decoupled software architecture, real-time data, and reactive programming [12].

L.K. Narayanan et al. (2020) developed " IoT water distribution networks" that incorporates "cloud and fog computing" for water distribution as well as underground pipeline health monitoring. The analysis was carried out using LSTM and ARIMA based on daily water use over three months. Compared to ARIMA, demand forecasting analysis utilizing LSTM gives higher accuracy with less error. In addition, a comparative analysis of demand forecasts is carried out to construct an adequate water supply network. [13].

2.1. Problem Statement

In none of the systems mentioned above the short-term daily water demand forecasts based on past daily water consumption data that is readily available was made. Furthermore, in a smart city idea, water demand forecasting is separate from the architecture of the WDN in order to distribute water efficiently and optimally to customers without wasting water.

As a result, in the following sections, we will analyze the idea of water distribution architecture based on IoT-based fog and cloud integration, followed by a detailed discussion of water demand forecasting and water distribution design.

3. Proposed Methodology

There are numerous independent systems in the real world for demand forecasting, water distribution automation, water distribution control, supply estimation, quality assessment, etc. However, each of these systems is tailored to a specific application. With the beginning of IoT and fog computing, IoT fog and cloud-integrated water distribution architecture are proposed. The goal is to supply a cost-effective and favorably reliable framework for water distribution and underground pipeline condition monitoring using hydraulic parameters and predicted water demand. Weather, season, rainfall, and the types of houses and their water requirements are all characteristics that can significantly impact the decision-making system that determines consumer demand.

3.1 Water Distribution Architecture using IoT

This effort seeks to remotely monitor the water volume in the tank by measuring the distance between the sensor and the tank's height. An ultrasonic sensor is required to detect the distance between the sensor and the tank's liquid level and to relay the sensor's data to the Arduino. Install flow meters on main and branch pipes to track each household's water consumption in their respective locations. The float switch is used in the subterranean water tank to open or close the solenoid valve in the bypass pipe based on the water level in the tank.

Figure 1 depicts the proposed block diagram's implementation. The high tank, in this case, is a 5-litre tank. An electric valve that operates on/off in response to a controller signal. The electric valve, in this case, is a 12-volt solenoid valve. The float switch prevents the water tank from overflowing and automatically indicates when the tank is empty.

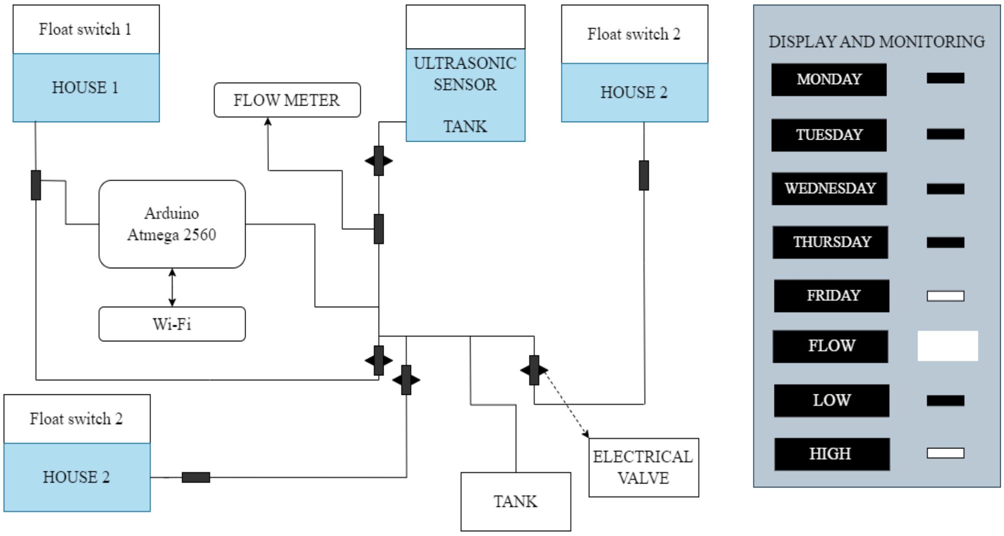

Figure 1. Block Diagram for Proposed System

Tank liquid levels are measured using ultrasonic sensors. This displays the distance in centimetres ranging from 2 to 450 centimetres.Then multiply by the proportion of water in the tank. An Arduino Atmega328p microcontroller is utilized in this example. The Wi-Fi Node Mcu ESP8266 module is used as a Wi-Fi adapter to bring wireless internet connectivity to the microcontroller via the UART interface, and it is used to monitor each household's water level, flow, and consumption. A flow meter measures the amount of water in the tank.

3.2 LSTM (Long Short-Term Memory) Architecture

This section goes over water demand forecasts in detail in order to effectively execute WDS design. Water consumption forecasting is accomplished by the use of LSTM, a form of "recurrent neural network" in "deep learning".

Hochreiter and Schmidhuber developed LSTM to develop recurrent neural networks that solved earlier RNN limitations by adding interactions to every unit (or module). LSTM is a form of recurrent neural network that can learn long-term dependencies and maintain information for an extended period by default. A basic LSTM system is made up of memory blocks called cells. The cell in the following row inherits two states: concealed and cell states. The state of the drive is the backbone of data transfer, and data can flow unmodified. Some

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linear transformations, however, may exist. Cell state data can be added or withdrawn using sigmoid gates. Gates are similar to layers with different weights or a sequence of matrix operations. By utilizing gates to control stored operations, LSTMs strive to avoid long-term dependency. LSTMs were chosen over simple RNNs since they have short-term memory, and it takes work to maintain knowledge from previous stages. So, to tackle this issue, employ LSTMS. Besides the cell states and gates utilized in LSTM, the procedure is nearly similar to a simple recurrent neural network.

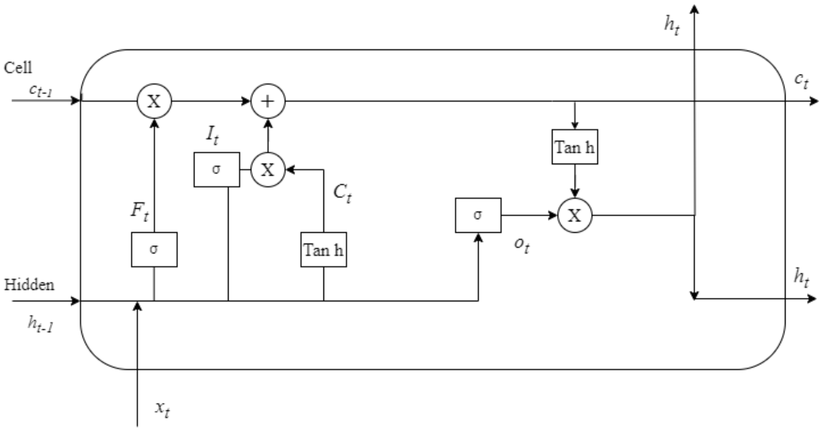

Figure 2. LSTM with Internal Structure

Data is kept in the cell state during the stream's processing. To add or remove data from the cell state, use gates. These gates are artificial neural networks that parse simple relation structures and choose which information to keep. Three gates determine the concealed state of the network: the entering gate, the forget gate, and the exit gate.

The data is multiplied by 0 will "forget" the output data, whilst multiplying it by 1 will "retain" the same information. As shown in Figure 1, if the present time interval is t and the given input value is xt, the output is hidden, denoted by ht, and the current state is ct. Make use of the hidden state h(t-1). The present state c(t-1) is the product of the forgotten state ft and the previously stored state c. The forget gate's output determines whether the previous memory cell's value should be discarded. If the value is zero, it is discarded; otherwise, it is maintained. Because it has a predicted value, the output gate determines the next concealed state. Use multiple activation functions to activate cells.

The sigmoid function is applied to h(t-1) and xt to determine the hidden state, and the tanh function is assigned to the new cell state, which is the product of the sigmoid function and the tanh output value. The present step's last hidden state is assigned to the following time step.

3.3 Water Demand Forecasting using LSTM

The water requirements in a particular condominium are forecasted based on the real time data that was collected from monitoring each household's water level, flow, and consumption for a year. The data consisted of maximum consumption of water collected through the water meters. The figure .3 below shows the water consumed, flow and the water level observed for total of 10 houses in condominium for a year.

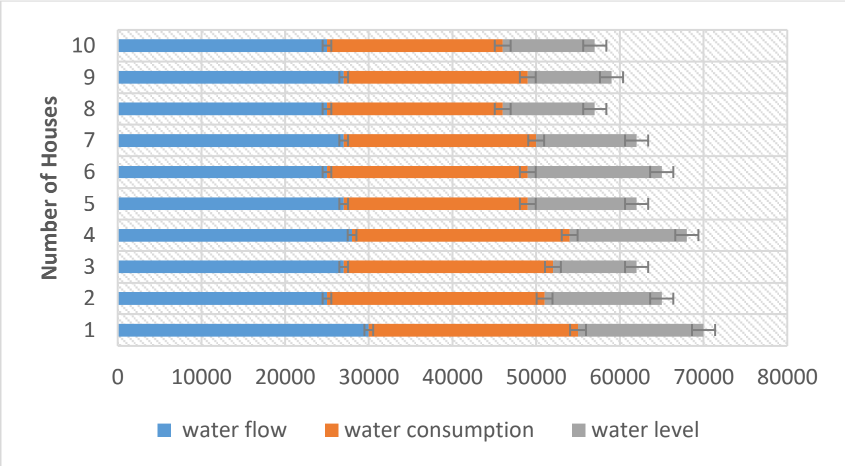

Figure 3. Water Consumption Details

4. Result and Discussion

This section describes the forecast analysis outcomes in terms of prediction accuracy and forecast error rate based on the dataset. The prediction for water demand is made with the help of the water consumption details of 10 houses observed for 365 days in a condominium. The dataset collected are loaded using the Pandas library in .csv format and the NumPy array. The experiment is carried out in SciPy environment with the Keras deep learning library installed. The dataset is prepared using the MinMaxScaler preprocessing class from the scikit-learn library and spilt for training and testing. 70% of the data was used for training and whereas 30 was employed in testing. The network was trained for 50 epochs and batch size of 1. The LSTM network has a visible layer with 1 input and hidden layer with 4 LSTM blocks and an output layer that does a single value prediction. Sigmoid activation functions are utilized for the blocks. The Table .1 below shows the accuracy observed in predicting the water demands and also shows its comparison with the existing models.

Table 1. Accuracy Evaluation

Algorithm	Accuracy (%)
Decision tree [14]	87
Random forest [3]	93.5
ARIMA [13]	96.8
LSTM	99.5

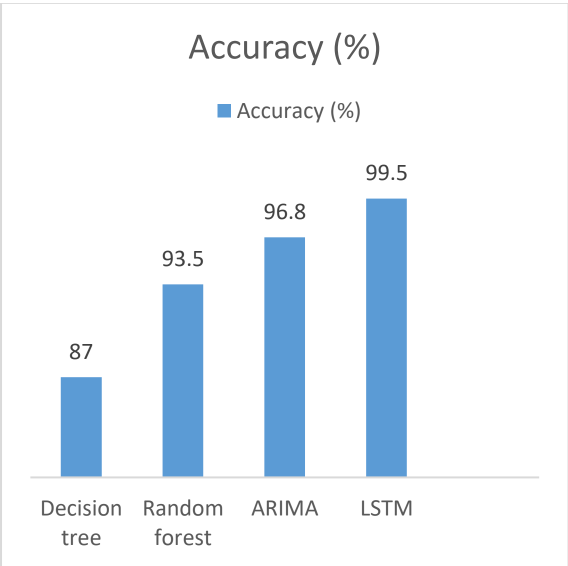

Figure 4. Performance Comparisons in Terms of Accuracy

To calculate accuracy, divide the per cent inaccuracy by 100. The LSTM model exceeds previous predictive analytics algorithms in terms of accuracy. When the complete dataset is validated, LSTM is nearly 99.5% accurate, whereas DT, RF, and ARIMA are 87%, 93.5%, and 96.8% accurate, respectively. Figure 4 depicts a graphical representation of the prediction accuracy.

Table 2. Mean Absolute Percentage Error Evaluation

Algorithm	MAPE (%)
Decision tree	70
Random forest	60
ARIMA	55
LSTM	30

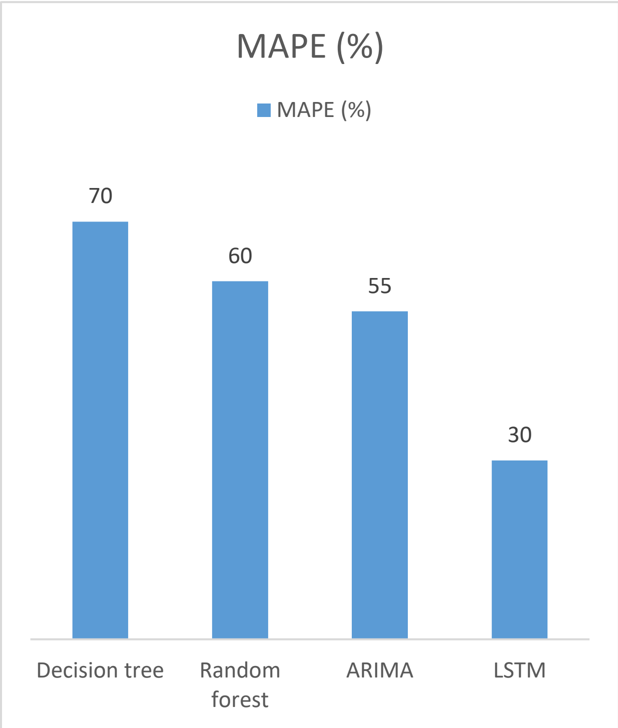

Figure 5. Performance Comparisons in Terms of MAPE

Figure.5 depicts a graphical illustration of the inaccuracy. Regarding actual and expected values for demand forecasting, it is evident that ARIMA, RF, and DT have higher MAPE errors than LSTM. Nevertheless, the forecast accuracy of the LSTM method is higher than that of the current prediction models, and the existing MAPE is higher than that of the LSTM, as shown in Table 3. The statistical study also revealed that consumption was high despite the forecasted demand. The consumer can partially utilize consumption.

Table 3. Training Time

Algorithm	Training time (sec)
Decision tree	85
Random forest	90
ARIMA	70
LSTM	58

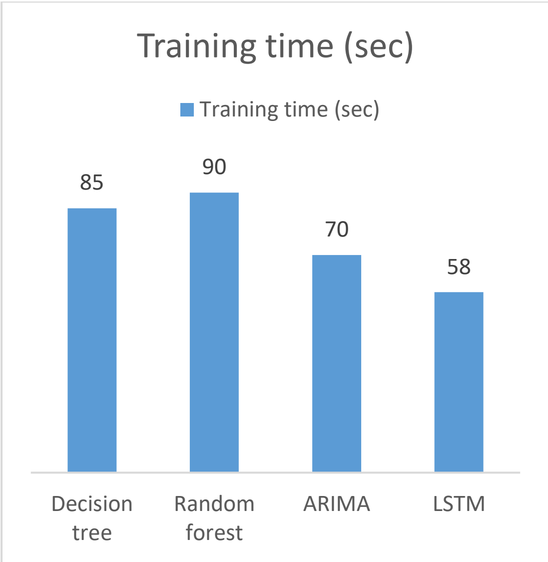

Figure 6. Performance Comparisons in Terms of Training Time (sec)

Figure 6 depicts the training period for every model as an XY plot. RF model is the most computationally expensive (train time: 90 seconds), and the DT model demands the most outstanding storage capacity (train time: 85 seconds). In this comparison, ML methods are commonly less expensive in computing time than DL methods.

5. Conclusion

Finally, an IoT-based water distribution framework, fog computing, and LSTM-based network design is suggested. In addition, a comparative demand projection analysis is also carried out to build an effective water distribution network. The analysis used LSTM based on daily water intake over twelve months. Compared to previous approaches, demand forecasting analysis utilising LSTM achieves higher accuracy and lower error. Based on the LSTM-based prediction results, the IoT-based system's water distribution system design intends to use hydraulic engineering to efficiently deliver water with little loss and consistent quality, thereby constructing a smart water distribution network in future.

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