Monitoring and forecasting water consumption and detecting leakage using an IoT system

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ABSTRACT

Water is an important resource for life and its existence and unfortunately, daily large quantities of water are being wasted. Monitoring the consumption of water can control water usage and smart technologies can play a useful role. In this paper, a smart system based on Internet of Things (IoT) has been proposed to monitor the water consumption in an urban housing complex. Ultrasonic Sensor along with Arduino continuously monitors the water level of the Water Tanks on Rooftops and sends this data to a server through a Wi-Fi module. Using the data collected from the IoT system, average water requirement by households are calculated (Daily/Weekly). Support Vector Machines (SVM) is used to forecast water consumption. The observed readings are divided into training and testing datasets. Water consumption is predicted for each day for a user. Error is recorded as the difference between the actual consumption and the predicted value, and it decreases as the number of days increase. An algorithm to monitor leakage of water in the tanks has also been proposed. A web interface allows the user to visualize the water usage, monitor his/her consumption, and detect any leakage and leakage rate in the system.

Key words | IoT, leakage detection, machine learning, smart water management, SVM, water consumption

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INTRODUCTION

Due to rapid urbanization and population increase, the stress on freshwater resources is ever increasing. This will have catastrophic impacts on food security and poverty (Sayre & Taraz 2019). So, proper techniques should be adopted for water conservation and technology can play an important role. Water should be used optimally, i.e., just for use and no wastage. Water losses, over-use, quality are some of the issues in Urban Water Systems. Information and Communication Technology can play a significant role here through the development of Smart water grids that network and automate monitoring and control devices (Mutchek & Williams 2014). With the help of smart technologies, not only can the water consumption be continuously monitored but also the user can be given control of their consumption. Real-time modeling and control of water distribution in a particular urban/rural region is principally guided by the water consumption data in the various households or a group of households and our methodology of estimating the water usage can play a useful role in this activity Also, large amount of water is wasted through water leakage in tanks and pipes. By detecting these leakages in water tanks and pipes, and notifying the user about the same, can be a step towards monitoring and control of wastage of water. Consumption of users was monitored using electromagnetic meters at an hourly time step and water losses were assessed w. r. t. the real case

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(Alvisi *et al.* 2019). Drivers, development and global deployment of intelligent water metering have been reviewed (Boyle and Giurco 2013). Smart metering helps water utilities to rapidly identify and take the appropriate action on significant volumes of post meter leakage occurring in cities (Britton & Stewart *et al.* 2013). A framework has been presented for the classification of residential water demand modeling studies (Cominola & Giuliani *et al.*
Q4 2015). Implications of smart water metering have been discussed for enhanced water distribution infrastructure planning and management and can be found in (Gurung *et al.* 2014) and (Luciani *et al.* 2019). Urban water demand management planning, policy and practice have been dis-
Q5 cussed (Willis *et al.* 2011).

The authors (Ishido & Takahashi 2014) have proposed a new algorithm, which proposes a technique for real-time leak detection in a water distribution network using real-time pressure measurements only. A proposal for design and development of a low cost system for real time monitoring of the water quality in IOT can be found in (Vijayakumar & Ramya 2015). A completely data-driven, fully adaptive, self-learning algorithm for water demand forecasting in the short-term and with hourly periodicity is proposed in (Candelieri *et al.* 2015). In (Shahanas & Sivakumar 2016), the authors have discussed in detail about the design of IoT systems and related analytics in the context of smart city initiatives in India. Machine learning techniques to smart city management aspects like smart water management which include water demand forecasting, water quality monitoring and anomaly detection has been detailed out in (Vijai & Sivakumar 2016). The research work suggests that the smart water management can be divided mainly into three parts: (i) forecasting demand, (ii) water quality monitoring and (iii) anomaly detection. A proposal for the design of water tank monitoring system based on mobile devices has been presented in (Gama-Moreno *et al.* 2016). The system is called 'Interface for Monitoring Water
Q6 Tanks (IRMA). The authors in (Maevsky *et al.* 2017) presented system analysis of Internet of Things and proposed a hierarchical architecture of smart systems. The research work provides future research directions of IOT systems.

In (Peña-Guzmán *et al.* 2016), the authors presented a model for forecasting water demand in residential, commercial, and industrial zones in Bogotá, Colombia, using least-squares support vector machines (LS-SVM) for forecasting water demand and explored the effectiveness of this model for long time scales. In (Jiang *et al.* 2017), the authors did a study of particle swarm optimization combined with SVM (PSO-SVM) model for daily water demand prediction. A proposal for using soft computing methods for forecasting water demands can be found in (Ghalehkhondabi *et al.* 2017). In (Gautam *et al.* 2018), the Q7
authors proposed an IOT based real time monitoring of water levels in tanks using machine learning and Android app. Analytics had been performed on Kaggle datasets, which was for 19 households in a society of Venice city.

In practicing prevention of leakage in Tokyo, Bureau of Waterworks, Tokyo Metropolitan Government (2018) observed that the water pipes embedded underground are constantly subject to a danger of leakage, and when leakage occurs, these pipes pose risks of factors like secondary disasters including poor water flow, sagging road, inundation and so on. As for these measures against leakage, 13 cities (including Tokyo, the host city, Seoul, Los Angeles and New York) agreed to make efforts to promote such measures. A proposal for leakage detection and estimation algorithm is presented in (Adedeji *et al.* 2017) for loss reduction in water piping net- Q8
works. Water loss through leaking pipes is a major challenge to the operational service of water utilities. There has been a lot of financial loss and environmental pollution caused by leaking pipes. The algorithm helps in the detection of critical segments or pipes of the network experiencing higher leakage outflow. A summary of popular leak detection technologies to help with through understanding this field of research can be found in (El-Zahab & Zayed 2019).

By focusing on the above research contributions, an IoT based Smart Water Management (SWM) has been proposed that involves an UV sensor and Arduino to detect water level in tanks. SWM includes data collection and integration using Ultrasonic sensor, data distribution using Arduino microcontroller, data analytics, forecasting and decision support using machine learning techniques. The sensed data from the UV sensor is sent to a server by the Wi-Fi device in the Arduino board, which can be monitored by the users using a web interface. The data set used here has been collected from the water tanks supplying water to 16 households in JSS Academy of Technical Education, NOIDA [https://jssaten.ac.in/academics/CSE/index.php], staff quarters. The next step after data collection is to apply proper analysis and optimization techniques to the data so that proper use of data can be done. This calls for the use of machine learning algorithms to monitor the collected data. SVM algorithm has been used to forecast the water demand.

An algorithm to check water leakage has also been proposed. The basic assumption in the algorithm is that for leakage to be detected, there is a need from the user to input if the water is in use or not, and if it's the former the leakage cannot be predicted. The leakage has been detected when the water is not being used as well as in the period when there is no water supply. Leakage rate has also been calculated.

Key contributions are:

1. An IoT based smart system development for monitoring water usage in an urban environment.
2. Proposal of a machine learning based technique.
3. Proposal for water leakage detection based on user input and water usage data.
4. Development of user end visualization tool for estimation, prediction and leakage detection.

METHODOLOGY

The various phases include data acquistion, communication, storage, pre-processing, analytics and a web interfaces.

1. Collection of water level (consumption) data from water tanks installed on rooftops at JSSATE NOIDA staff quarters.
2. Performing pre-processing steps on the data.
3. Performing analysis on the data; applying SVM for forecasting water consumption, leakage detection and leakage rate.
4. Designing a web interface for the users for visualization purpose.

This research work has been performed on the rooftops at JSSATE NOIDA staff quarters in the state of Uttar Pradesh, India. There were 2 sets of tanks, each set containing 2 tanks and two tanks in a set were interconnected. Tank 1 had two tanks, which was RO water used for drinking and cooking purposes. Tank 2 had 2 water tanks in which water was used for other household activities. In total, there were 4 tanks. The setup (Figure 1(c)) was installed on the tanks,

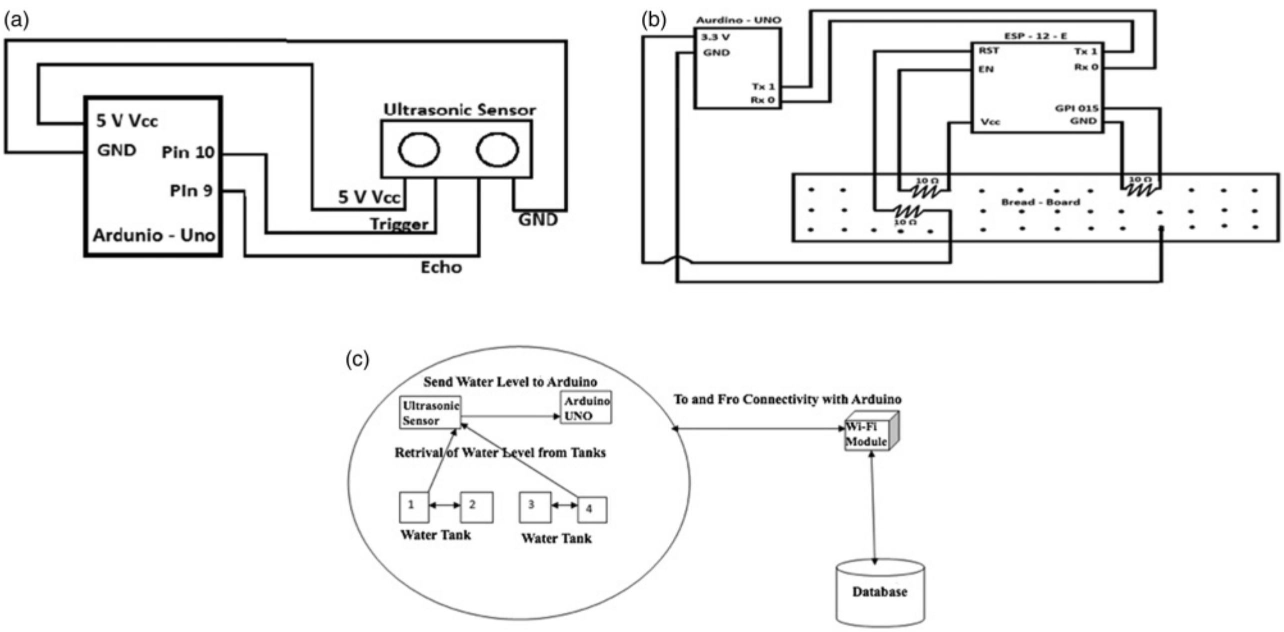


Figure 1 | Overall System Architecture: (a) Interfacing of Arduino with Ultrasonic Sensor (b) PIN Diagram of ESP (Wi-Fi Microchip) module with Arduino (c) Data Communcation of Arduino with the Database Server. Q15

which were connected to 16 households comprising of 24 people in all. The detailed system architecture has been given in the sub-section 2.a. The initial and the most essential part of our project is data acquisition, which is explained in the sub-section 2.b. The circuit diagram of Arduino with ultrasonic sensor (Figure 1(a)) performs data acquisition, ESP module with Arduino (Figure 1(b)) does data communication and finally data is stored on a server (Figure 1(c)). We describe the pre-processing of data in sub-section 2.c, i.e. Intervals of time, the data is taken and handling of missing values. The next sub-section 2.d deals with analytics part, i.e., about the features taken, applying SVM algorithm and Leakage Detection algorithm. Finally, in sub-section 2.e we brief about the various user interfaces, starting from Login Page, OTP Verification Page, Interface to upload CSV file for datasets, list of attributes, the interface for total water consumption, total number of users and average consumption for a user in a day, user interface for predicted value of water required on the next day per user on basis of previously observed water usage. The purpose of the entire methodology is to provide the users the forecast of their water usage and also to inform about leakage detection through a well-suited web interface.

System architecture

Below, a list of the hardware components has been provided along with technical specification of the ultrasound sensor and an illustration of the sensor and data acquisition architecture, the ultrasound sensor and the wifi.

Sensor and data acquisition hardware

- 1 × Breadboard
- 1 × Arduino Uno R3
- 1 × ULTRASONIC Sensor (HC-SR04)
- 1 × LCD 16 × 2
- ESP Module
- Connecting Wires

Technical specifications for ultrasonic sensor

Power Supply – +5 V DC
Quiescent Current – <2 mA
Working Current – 15 mA
Effectual Angle – <15°
Ranging Distance – 2 cm – 400 cm/1″ – 13ft

Data acquisition, communication, storage

The data used for the project was collected from a housing complex having 16 households. The height of the water tank as well as the requirement of the household plays an important role in determining the working of the whole process of starting and stopping the motor. The water tanks installed were Syntax 1,000 L tanks having 109.98 cm radius and 122.43 cm height. There was no inflow of water in the tanks at the time of monitoring. The tank system is as shown in Figure 2.

Working of ultrasonic sensor

The Arduino kit including the UV sensor was installed on the top of one of the two tanks, to monitor the water level after every 10 seconds. This ultrasonic sensor sends UV rays to measure the distance of water level from the top of the tank using SONAR. The sensor sends the ultrasonic waves to water level, which is reflected by the water surface and comes back to the ultrasonic sensor. Sensor uses this time of wave propagation to calculate the distance between the sensor and the water level. Time taken by the pulse is actually to and fro for travel of the ultrasonic signals, while only half of this is needed. Therefore, the time is time /2.

Distance Calculation:

Distance = speed*time/2

Speed of sound at sea level = 343 m/s or 34,300 cm/s Thus the distance measured = 17150* time (unit cm) Boyle *et al.* (2013).

With the help of that distance, the water level and hence the volume of water consumed can be calculated since the height and radius of the tank are fixed.

Working of arduino board

The Arduino is programmed by sending a set of instructions to the microcontroller on the board. The water level monitored by the Arduino kit is continuously sent to the server using the WiFi module installed on the kit. The transfer of

Figure 2 | The water tank system used for data collection.

data in the system is as shown in the architecture in Figure 1(c).

Working of Wi-Fi module

The Wi-Fi module can connect to internet via hotspot by using its SSID and Password. It has been programmed to implement logic statements as per requirements of the project. The ultrasonic sensor reads the distance of water surface and returns it to the module. The module, when connected to internet, uploads this value to the database. The water level to be monitored for each tank is collected by the ultrasonic sensor and simultaneously the data collected is shifted to the server via ESP12-e.

Calculations of the current water level will be done using the given height of the water tank

In the data set, the *water level detected (W)* is the distance between the ultrasonic sensor and the water surface in the tank (i.e the height of the empty space in the tank).The *water height (w)* is the actual height of water in the tank (i.e the height upto which water is filled in the tank), which is calculated by subtracting the *water level detected* from the total height of the water tank (h cm) (Equation (1)).

$$\textbf{Water height}\ (\textbf{cm}.) = \textbf{Total height}\ (\textbf{cm}.) - \textbf{water level detected}\ (\textbf{cm}.) \quad (1)$$

Data description and pre-processing

Time step

The time step denotes the time difference in which the consumption on water have been recorded. Time step for a model is decided by the purpose for which the model is being used. The model can be for hourly basis, daily or monthly. In our system, the time-step is 10 seconds.

Handling missing data

In order to fill up the missing data, the mean values have been taken from the observed data. This was done after observing that consumption values did not vary greatly at nearly same temperature. The data was recorded for 21 days on an average of 4–5 hours daily with a total of 102 hours of readings being noted. The readings were taken on the same time intervals on different days.

Data analytics

Feature space and response variables

We have considered the following parameters in defining the feature space for the SVM algorithm:

(a) Volume of water consumed (cu cm), (b) Number of users, (c) Temperature (C) and (d) Precipitation (mm).

The response variables for SVM consist of:

(a) Average Water Consumption per user per day and (b) Prediction of Water Consumption per user per day.

The algorithm for leakage detection considered the following parameters:

(a) Input variables are Water Level Initial, Water Level Final and InUse.
(b) Response Variables include Leakage detected (yes/No) and Leakage Rate (cubic cm/sec).

SVM based classification

SVM has been used for analysis purposes, since it is highly accurate and the preferred method for data sets with small size [Ray 2017]. SVM is also less prone to over fitting than other methods and facilitates compact model for classification. Kernel Function, radial basis function (RBF) is used since the data is not linearly separable [Ng 2020] and is the most commonly used kernel in support vector machines. Finally, the optimal hyper-plane is found, which makes maximum empty spaces at two sides of coordinate. The independent variables used for training are shown in Table 1.

Next, the model parameters in designing the proposed SVM classifier are described.

If a set independent variable is $\vec{x}_i = (x_{i1}, x_{i2}, \ldots, x_{in})$ and water demand is $q_{i,}$ the SVM model equation can be written as Equation (2):

$$\vec{q} = \frac{1}{2}\sum_{i,j}^{l} \alpha_i\, k(\vec{x}_i, \vec{x}_j) + \beta \tag{2}$$

where q is the series of water demand prediction values. α_i is the undetermined parameters with the Equation (3).

$$\alpha_i = C\xi_i \tag{3}$$

where C is penalty factor, ξ_i is slack variable, k is the kernel function, RBF (Radial Basis Function), and σ is extension constant of RBF (Equation (4)).

$$k(x_i, x_j) = e^{-|x_i - x_j|/2\sigma^2} \tag{4}$$

Table 1 | Input parameters

Variables Id	Variables Name
X_i	Set of independent input variable
C	Penalty Factor
σ	Extension constant of RBF
α	Extra Undetermined parameter
k	Kernel Function
β	Offset Value for SVM
V_i	Volume of water consumed (cu cm.)
T_i	Temperature (degree C)
P_i	Precipitation (mm)
N_i	Number of users
q_i	Series of Water Demand Prediction Values (From 8th day onwards)

Steps for the training algorithm

Step 1: We divide the dataset into two sets- training data and testing dataset. As we have data for around 25 days we take the initial 7 days i.e. from 03/02/19 to 10/02/19 days data as training data.

Step 2: From the next day i.e. 11/02/19 we predict the total consumption values using the training dataset by applying the SVM algorithm.

Step 3: The predicted value for the 8th day is compared with the actual water consumption value for that day. The Error value is calculated by finding the difference between the actual and the predicted value.

Step 4: Now for predicting the consumption value for the next day i.e for the 9th day we take the 8 days value in the training dataset. This is recursively repeated and we predict the value for n^{th} day by using the previous n – 1 days values in the training data set.

Step 5: Each time we increase the dataset for training data the error value shows a significant reduction i.e. we approach toward a more accurate prediction.

Steps to implement SVM (predicting the water consumption on the next day, i.e., using 7 days data for learning and increasing the number of days for learning. Calculate the error)

Step 1: Input independent input variable x (Temperature, Precipitation) and water demand as output y series (predicted water demand value).

Step 2: Normalize the x and y series.

Step 3: Randomly create C (Penalty function) and σ (Extension Constant) and input the SVM model. PSO model is used to optimise C and σ. The values are iteratively optimized to improve solution. Reusing Equation (3) for convenience.

$$\alpha_i = C\xi_i$$

Step 4: Using CV-5 model, train this model and calculate error E. The dataset is divided into 5 parts using CV-5 Xu & Goodacre (2018) model. Here one part of data set is taken as test data and the rest is the training data set. Then a model is fitted and error E is calculated each time (Equation (5)).

$$E = \sum_{i=1}^{V} \frac{1}{2}\sum_{t=1}^{T} (y_t - y'_t)^2 \qquad (5)$$

Step 5: If E is up to the criterion Goto Step 6 Else Goto Step 4.

Step 6: Output the parameters α (undetermined parameter used in the prediction value equation) and β (offset value) of SVM.

Step 7: Input new independent x_1 (The next group of test data).

Step 8: Predict the new water demand in y'. Using Equations (2) and (4).

To implement SVM, Java Machine Learning Library (Java-ML) is used. Java-ML is a collection of machine learning algorithms with a common interface for algorithms of the same type. Java-ML contains algorithms for data preprocessing, feature selection, classification, and clustering. In addition, it features several Weka bridges to access Weka's algorithms directly through the Java-ML API.

Following are the libraries that have been used in the implementation (http://java-ml.sourceforge.net):

- net.sf.javaml.clustering: These are clustering algorithms such as k-means, self-organizing maps, spatial clustering, Cobweb, AQBC, and others
- net.sf.javaml.tools: These are utility methods on dataset, instance manipulation, serialization, Weka API interface, and so on
- net.sf.javaml.utils: These are utility methods for algorithms, for example, statistics, math methods, contingency tables, and others
- net.sf.javaml.classification: These are classification algorithms, including naive Bayes,
- random forests, bagging, self-organizing maps, k-nearest neighbors, and so on

Minimizing forecasting deviation

Measuring forecast errors is crucial for the selection of an accurate and reliable forecasting model.

The basic step consists in comparing forecasts with observations, possibly by using a wide sub-set of the available data to learn/build the forecasting model and the remaining sub-set of data to validate it.

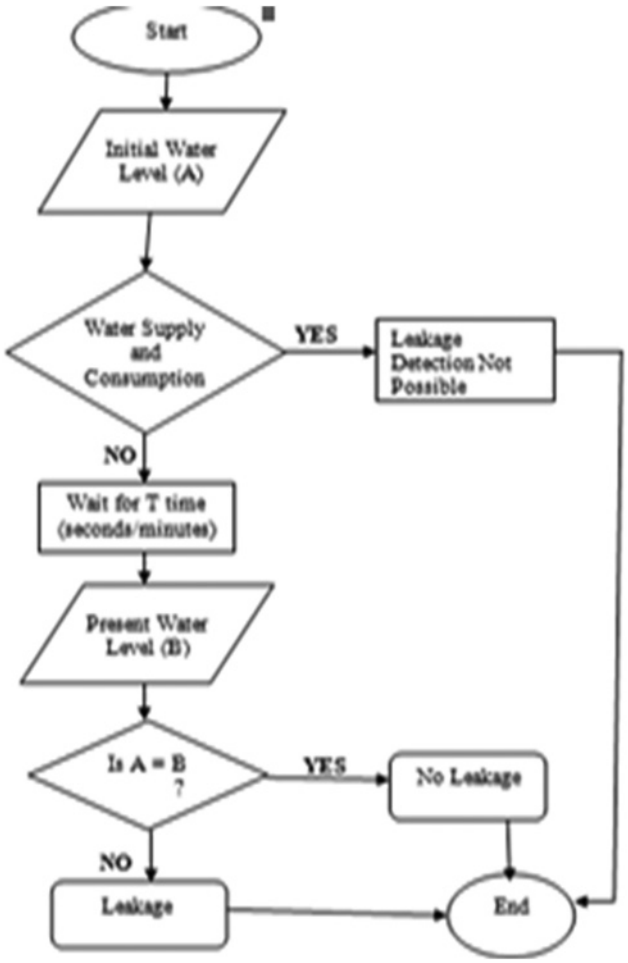
The most widely adopted error measures is MAPE (Mean Absolute Percentage Error) (Equation (6)).

Y – time-series of observed water demand (at any forecast periodicity)
Y_t – water demand observed at the time t
Y average of the water demand observed
$\hat{Y}$ – time-series of forecasted water demand (at any forecast periodicity)
$\hat{Y}_t$ – water demand forecasted at the time t
N – time-series length

$$MAPE = \frac{100}{N}\sum_{i=1}^{N} \left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \qquad (6)$$

Algorithm for leakage detection

The Leakage detection system is another major feature of this project. Water Leakage is a major cause of unwanted water loss, which needs to be avoided. It can monitor and controlled only by detecting the leakages at the first place. At the basic level, the proposed Leakage Detection algorithm illustrated in Figure 3 can detect leakage in household. The important condition is that the Water Supply should not be ON and none of the users should use Water, when the leakage is being detected. Initially, the initial water Level (A) is noted. And, after T time (which can be in seconds/minutes), Present Water Level (B) is noted. If A = B, there is no leakage,



Q16 **Figure 3** | Leakage Detection Algorithm.

otherwise, leakage is notified and rate of leakage is calculated. It provides a message notification to user in case if any leakage is detected in the tank and they can take actions accordingly. The rate of leakage **r** is calculated using the formula (Equation (7)):-

$$r = (\boldsymbol{v}_2 - \boldsymbol{v}_1)/(\boldsymbol{t}_2 - \boldsymbol{t}_1) \tag{7}$$

where $\boldsymbol{v}_2$ is final volume, $\boldsymbol{v}_1$ is initial volume, $\boldsymbol{t}_2$ is final time and $\boldsymbol{t}_1$ is initial time.

User interface design

Iorder to make the system more users interactive, the project includes a user interface for our smart system. The users can enter the required data including number of current users, water in use or not. Further processing and results are shown based on the user input.

The interfaces are shown in Figures 4–6.

Figure 4 shows the Interface for Total Water Consumption, total number of users and average consumption for a user in a day.

Figure 5 demonstrates user interface for predicted value of water required on the next day per user on basis of previously observed water usage, so that user can get a forecast of their water usage.

Figure 6 shows the snapshot of web interface for leakage detection system where it shows whether leakage has been detected or not and if in case, leakage is detected then the rate of leakage is been displayed.

RESULTS AND DISCUSSIONS

The graph between the Average Calculated Values and Predicted Values Versus Number of Days is plotted and is as shown in the Figure 7. The result is susceptible to many factors like holidays, temperature, weather etc. Clearly the graph in Figure 7 shows that the predicted values and the Calculated Average Values tend to coincide as the data value increases.

The difference between the predicted and the actual values i.e the error value graph is as shown in the Figure 8. We found a maximum error of 46.75%, which was reported in the beginning when training dataset was small. The average error is around-11.34%.The minimum value of error is as low as −1.856%. As the training data set increases, the error value approaches to minimum.

CONCLUSIONS AND FUTURE DEVELOPMENTS

Water Wastage has become a huge problem now days, so this paper proposes IOT based water management system for collection of data and calculation of predicting average requirement of water per person, in a household and in a society and monitor his/her consumption. An algorithm to check for leakage detection has been proposed to calculate the rate of leakage and a web interface allows the user to

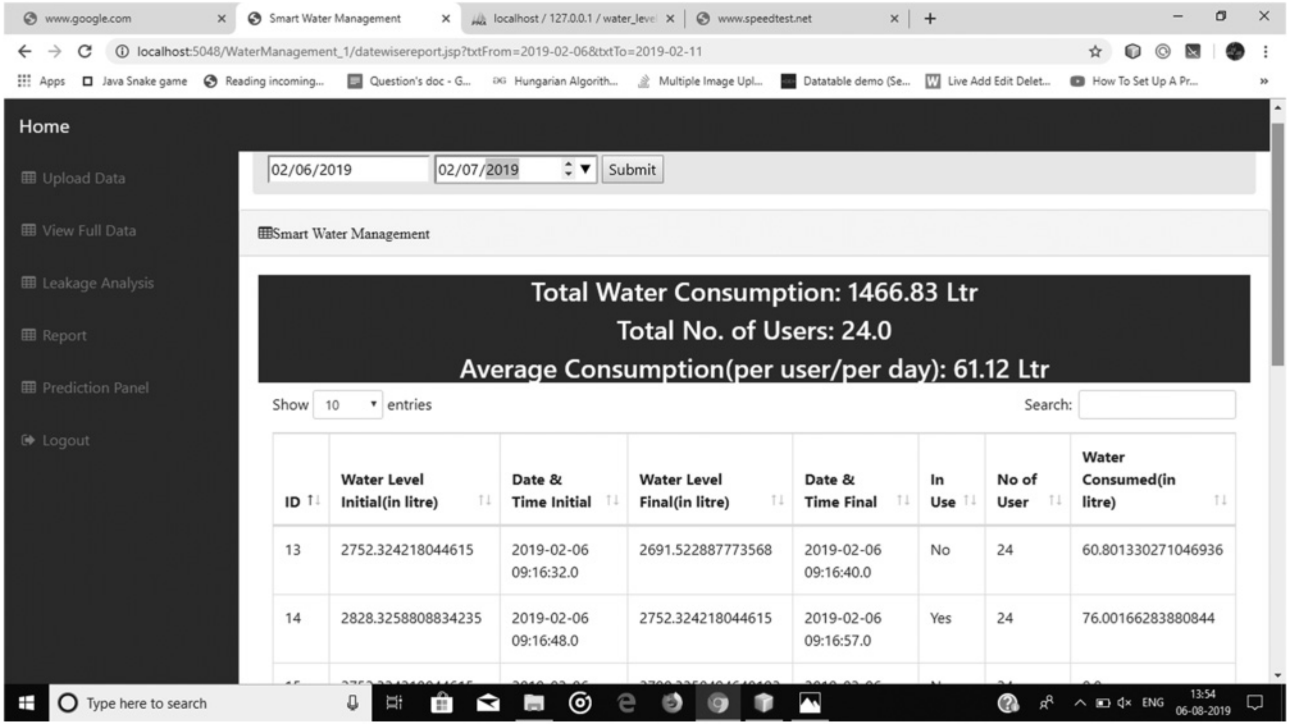


Figure 4 | Interface for Average Water Consumption by a user in a day.

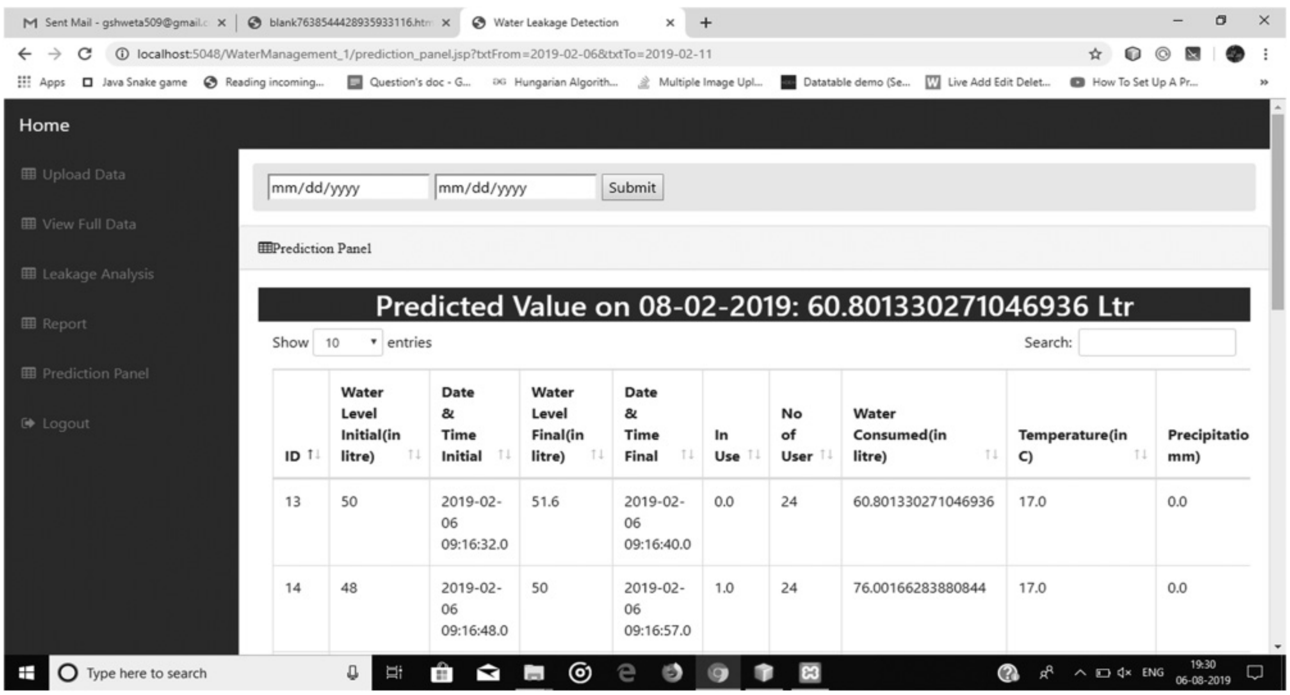


Figure 5 | Prediction of Water for Next Day.

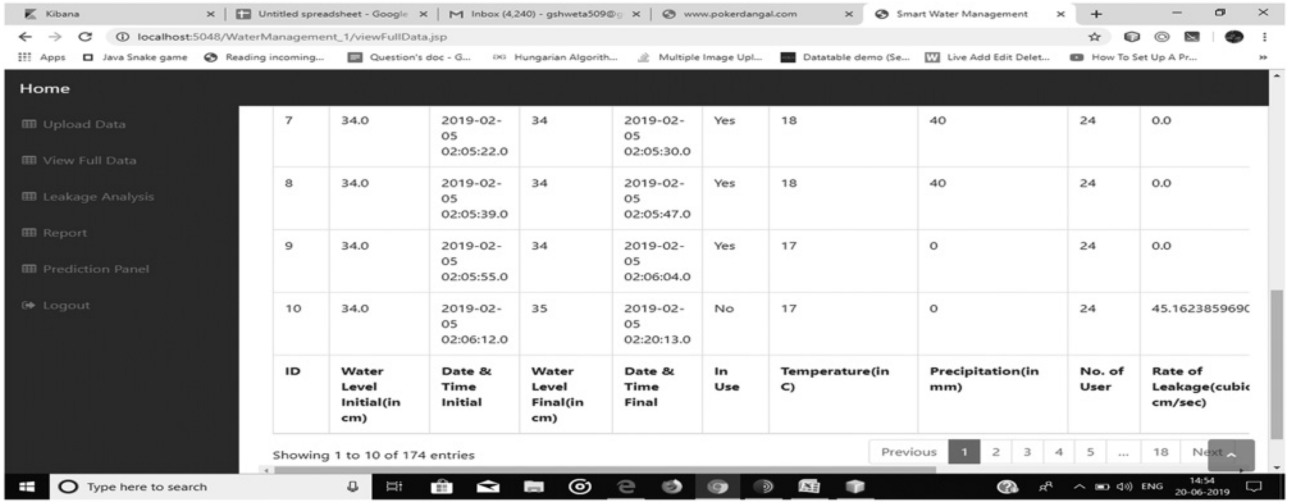


Figure 6 | Leakage Analysis Interface2.

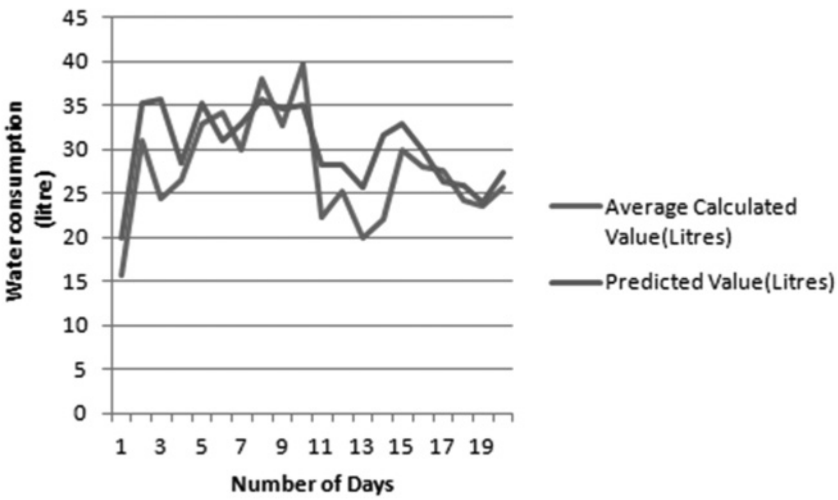


Figure 7 | Graph between Average Calculated Values and predicted values. Q17

Q18 **Figure 8** | Graph showing error on various dates.

visualize the water usage. The results show us that the error between the predicted and actual values is reduced as the size of dataset increases.

Future scope

If data is collected continuously over a year then average daily, weekly, monthly and yearly consumption of water can be calculated and more accurate water consumption values can be predicted.

If large dataset values are recorded, relation of water consumption with weather, relation of water consumption with holidays can be found and so on.

Application

The system is highly applicable for Urban Water Management. Helps to determine Water requirements in a society/ complex. Helps to calculate the Supply/Demand relationship. It helps to detect leakage and leakage rate. So that, immediate action can be taken to correct the causes of leakage, thus saving Water.

Advantage

1. It saves Water and reduces its loss due to unavailability of proper checks.
2. Saves a lot of users' efforts to check the level of Water Tanks.
3. Equal distribution of water for all (Chatterji & Haq 2019).

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