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Research Article

Dynamic water monitoring and management system using labview and machine learning

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ABSTRACT

Water plays a pivotal role in everyone's life. Water is necessary for all life to exist and grow. However, people frequently take its availability for granted, despite the fact that water is essential to existence. There are several problems regarding water that is concerning and needs to be addressed. In a residential area, the primary issues faced include water shortage, wastage of water, supply of poor quality water, ineffective water monitoring system, etc. All of this leads to poor water management and thus the residents suffer. Thus it's critical to develop an effective water monitoring and management system for proper water management. In this paper, the problem is addressed and solution is provided through dynamic water management system using LabVIEW and machine learning. the system offers predictive capabilities that allow users to estimate the total duration till the current volume of water is completely exhausted (available hours of water supply) and total duration till the tank refills completely (tank refill duration) based on the current water level in a tank. The main aim is to build a system that not only minimizes wastage of water but also enhances the overall effectiveness of water management. The data set was generated using LabVIEW software which simulated a water management system similar to the real world environment. Linear Regression machine learning algorithm was selected and applied to the data set for prediction of the required variables and the result obtained has 94.56% and 99.24% accuracy for Available Hours of Water Supply and Tank Refill Duration respectively. This system not only minimizes wastage of water but also enhances the overall effectiveness of water management.

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INTRODUCTION

Water is supplied to the housing societies by the Municipality every day. This water is directly stored in the underground tanks for storage purposes. At proper intervals, water is pumped to the overhead tanks of respective buildings to provide water supply to individual homes. Since the level of water in the tanks is not monitored, there

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is a tendency for overflow or underflow of water, resulting in wastage and other water management problems. Also, often times, due to a water shortage, there are situations where less or no water is supplied by the Municipality on certain days. Thus, it becomes crucial to have knowledge of how many hours of water will be available based on the current water level or amount. This piece of information also remains important in terms of pumping water to overhead tanks so as to not exhaust the current volume of water carelessly. Therefore, there is a requirement for constant water level monitoring and management and predicting the availability of water supply in hours based on a certain water level. In this paper, the ultimate focus is on dynamically monitor and manage the water level in tanks and predicting the available hours of water supply along with tank refill time with the help of data taken from LabVIEW and implementing it with Machine learning. LabVIEW is an environment that simplifies hardware integration for engineering applications so that you can simulate your hardware to acquire data from NI and third-party hardware. The data obtained from this software can be treated as coincidental to the data obtained from an original hardware system. This software helps greatly in monitoring the current water level of individual tanks, thus preventing overflow or underflow of resources. Also, the data regarding water levels obtained from the simulation contributes largely to the prediction of available hours of water supply and tank refill time with the help of machine learning.

Different Water Management Systems, people are using for effective use of water. Durga et al. [1] developed by the system by identifying water flow in the main pipe line using a water flow sensor, informing the Arduino. If power is available, the system checks the water level in the tank using an ultrasonic sensor. If power is not available, the user is informed via SMS. If the water level is not up to MAX, the system triggers a motor to fill the tank. The incoming water line and power supply are monitored and alerted by the system, if the supply is stopped. Data collected in the cloud helps analyze water consumption and take necessary actions for future use. Johari et al.[2] developed the system for Students' hostels and observed, power failures can cause water levels to decrease, especially during weekends and public holidays. To prevent unexpected water shortages, a monitoring system is developed to alert the technician or person in charge. The system consists of water level detector circuitry integrated with a GSM module, sending SMS for further action. Rao et al. [3] design and developed automatic water level controllers to control the motor, ensuring a constant water reserve in the storage tank. The developed system automatically fill the overhead tank, monitor water levels, and start the motor when the water level drops below a certain level. They also shut off when sump water runs out before filling the upper tank or if the pump is dry. The system is versatile and can control multiple pumps or tanks. The carbon water level sensor provides contact water level measurement. The automatic system operates the water pump without user interaction, eliminating the need for manual pumping. The system can be implemented at home or college using less expensive components. Automatic controls on water levels can minimize energy use, reduce water and energy loss, and prevent motor drying out, ensuring its longevity.

The systems developed by Ahmed et al. [4], and Herath et al. [5] , were based on machine learning which includes various algorithms that enables machine to make accurate predictions for particular tasks. There are two main types of Machine Learning: Supervised and Unsupervised learning. Supervised learning includes two categories: Classification and Regression. The main goal of the supervised learning technique is to map the input variable(x) with the output variable(y). Unsupervised learning focuses on grouping the objects based on the similarities, differences etc. Popular Machine Learning algorithms are Linear Regression, Convolutional Neural Networks(CNN), SVM etc. In the beginning, Prophet algorithm was selected to train the machine with the obtained data set. But the main drawback was that it required large datasets for training because of which ARIMA model was then selected. The same problem continued with ARIMA. Therefore, Linear Regression was finalized as it works well with the available datasets and produces the required result. The main aim of linear regression is to minimize the gap between predicted values and observed values.

Currently, there are several water controller systems [6], [7], [8] , already existing in the market but most of them have some limitations in practice making the system inefficient. The main limitations of the existing systems are

i. Existing systems lack the capability to calculate and forecast the Available Hours of Water Supply accurately.
ii. They also lack the capability to calculate and forecast the Tank Refill Duration.
iii. The capability to predict future water availability accurately is absent in these systems.
iv. All the systems have complex interfaces that limits the accessibility for border use bases.
v. Most of the system have manual monitoring and intervention, leading to delays and potential issues.
vi. All the systems work on the fixed flow rates, leading to inefficient resource utilization.
vii. Existing systems lack adaptability and struggle to cope with changing demands or unexpected events.

Hence, an attempt to overcome these limitations and increase the efficiency of the system was made by implementing a dynamic water monitoring and management system using LabVIEW and machine learning. To address these limitations, the system was designed and developed such that, given the level of water in the water tank, the hours of water availability can be predicted. The system is also developed to predict the duration for complete refilling of the tank. A simple user interface is created such that users can gain access to the water management system in an effortless fashion. Variable flow rates are supported in the system, thus taking into consideration the various scenarios and conditions of water management and supply. With the help of Machine Learning, adapting to the changing trends and unexpected demands or events of the system can be fulfilled.

MATERIALS AND METHODS

Data Generation Using Labview

The main aim was to develop a system which can predict the future water availability accurately. For this purpose, the system makes use of :

- LabVIEW - to create the required data set.
- Machine Learning Algorithms - to make proper predictions based on the obtained data set from LabVIEW.

In order for the machine to be able to estimate the Available Hours of Water Supply and Tank Refill Duration prediction based on the water level in a tank, a dataset is required. However, a pre-defined dataset related to the system was not available on the internet. For this purpose, LabVIEW software was used to simulate a similar water management system and thus generate the required dataset for different conditions. Once the dataset was ready, Machine Learning algorithm was used to train the machine and predict the Available Hours of Water Supply and Tank Refill Duration based on the water level in a tank.

LabVIEW stands for Laboratory Virtual Instrument Engineering Workbench. It is a visual programming language and development environment utilized for creating applications in measurement, automation, and control systems [9]. It enables users to design programs graphically by connecting virtual instruments, facilitating tasks like data acquisition, analysis, and instrument control across various engineering and scientific domains. LabVIEW consists of two primary panels: Front panel and Back Panel. Front panels are used as the user interface on which controls and indicators are constructed. Back Panels are used to develop graphical code by representing program logic with nodes and wires. Icons in the front panel are connected to the nodes in the back panel using wires. If the changes are made in front panel correspondingly it gets updated in the back panel.

Labview Front Panel

Fig 1 shows LabVIEW front panel structure. It includes:-[Text Wrapping Break]Two tanks - underground tank and an overhead tank. Water is supplied to the underground tank from Municipality. The connection is structured such that the outlet of the underground tank is connected to the inlet of the overhead tank. Finally, the outlet of the overhead tank is connected to the households.

There are flow-in and flow-out controllers which are used to control the flow-in and flow-out rates of the water. There are total 4 controllers (2 for underground tank, 2 for overhead tanks) and 4 indicators to show the current readings of flow rates. There are current water level indicators which show the current water level in the tanks. Cut-off activation indicators are colour indicators used for automating water supply cut-offs based on critical threshold values. For underground tank, if the water level goes below 1000 Litres, the lower indicator turns red and if the water goes above the 9000 Litres, then upper indicator will turn red otherwise it remains green. Similarly for the overhead tank, the minimum critical level is 100 Litres and the maximum critical level is 900 Litres. If the lower indicator turns red, it will automatically stop the water supply from the underground tank to overhead tank and if the upper indicator turns red it will halt the water supply. Further, there are two forecast indicators which show the Available Hours of Water Supply and Tank Refill Duration based on the water level in a tank.

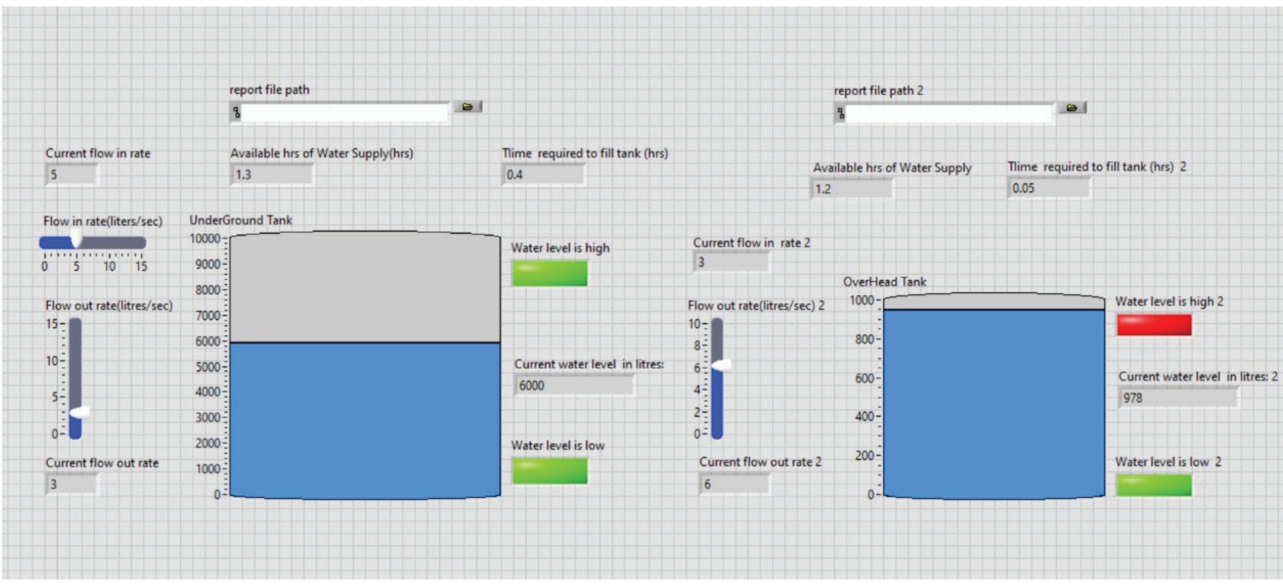


Figure 1. Front panel structure of LabVIEW.

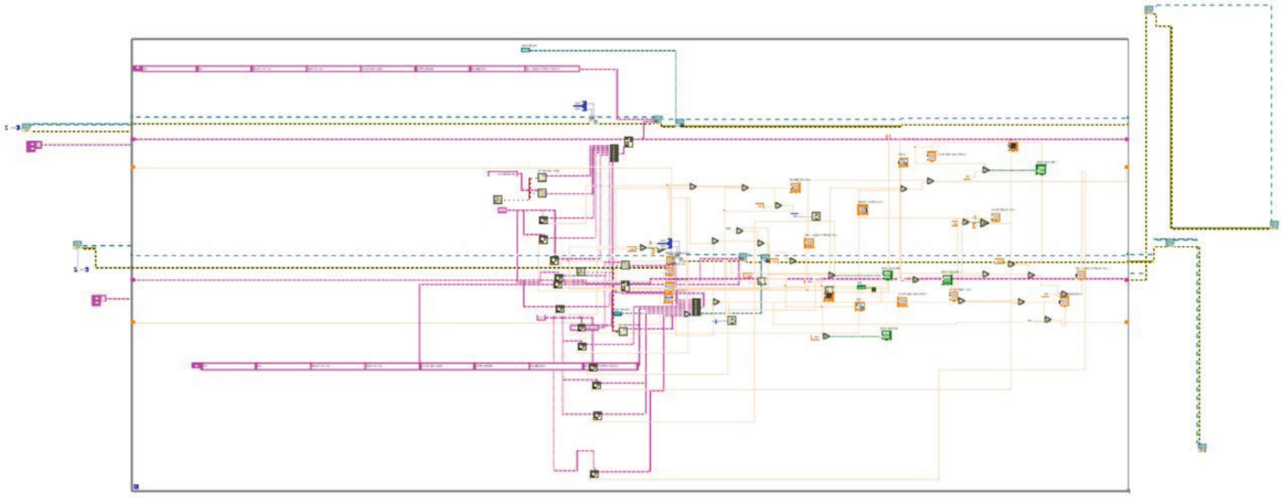


Figure 2. Architectural block diagram of LabVIEW.

Labview Block Diagram

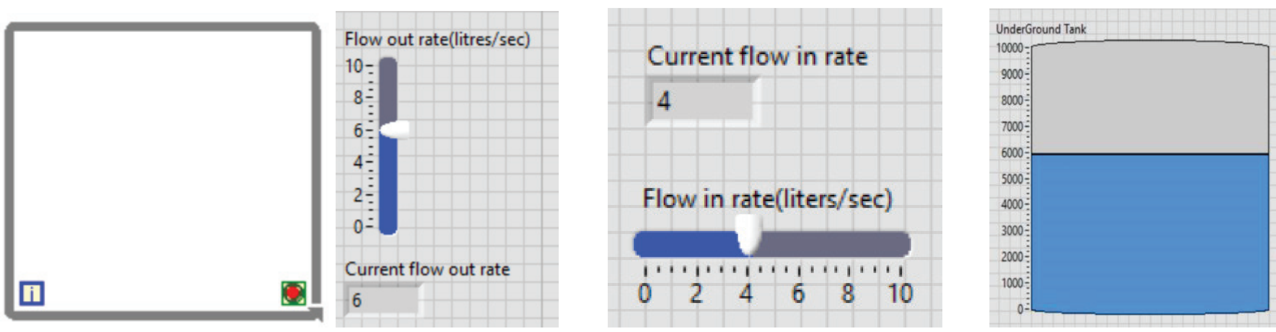
Fig. 2 shows back panel structure. It includes, entire logical representation of the icons, controllers etc. placed in the front panel in the form of Block Diagram. The output nodes are connected to the Front Panel indicators and wires link the Front Panel controls to the appropriate nodes on the Block Diagram. When any value updates on the front panel, it is sent through the wire to the node in the back panel.

BACK PANEL BLOCK DIAGRAM TOOLS

Tools used for developing dynamic water controller system. Figure 3 shows the various components/tools used in LabVIEW to generate the front panel of the system.

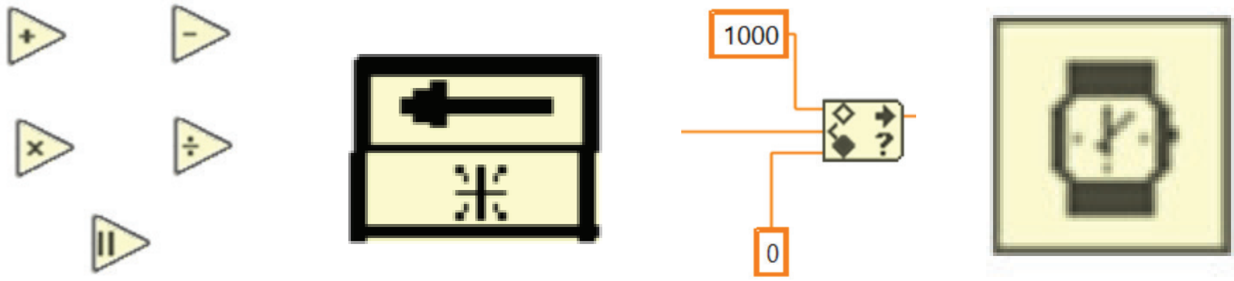
Figure 3 (a) shows the While loop component. The code within the while loop is repeated until a specified condition is met. A While Loop always runs at least once. For continuous execution, the entire code is placed in a while loop. Figure 3 (b) shows Flow rate controllers for varying the rate of flow of water into and out of the tanks. Flow rate controllers are horizontal and vertical pointer sliders. Sliders are used in the software to change numerical values. The tank component is shown in Figure 3 (c). To simulate the water tanks and display the numeric level, the tank function is used for developing program. The flow rate controls and current water level monitor are attached to the underground and overhead tanks in order to monitor and control the water levels in the tank.

Figure 4 (a) shows a numeric component. It functions as a numeric operator and is used to execute basic operations on numeric values, numerical functions are employed. Figure 4 (b) shows a Feedback Node. It acts as a memory register and stores data from one VI execution or loop iteration to the next. Figure 4(c) shows an In range component. The main function of this component is to determines whether x is inside the range defined by the upper and lower limits, and optionally coerces the value to be within the range. The underground tank's range is fixed to be at 0-10,000 and the overhead tank's range at 0-1000. Figure 4(d) shows a Wait component. It waits the specified number of milliseconds and returns the value of the millisecond timer.



(a) (b) (c)

Figure 3. (a) While loop (b) Flow rate controllers (c) Tanks.



(a) (b) (c) (d)

Figure 4. - (a) Numeric (b) Feedback node (c) In range (d) Wait.

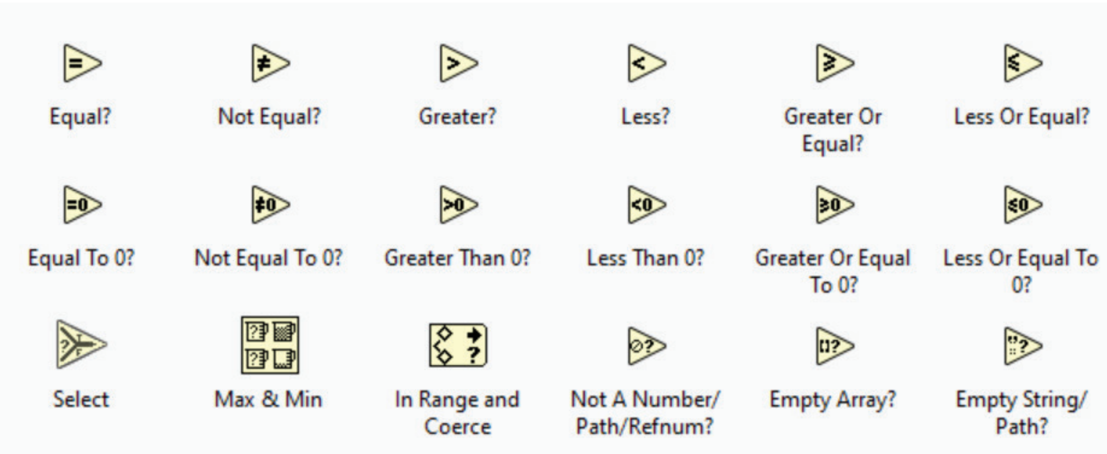
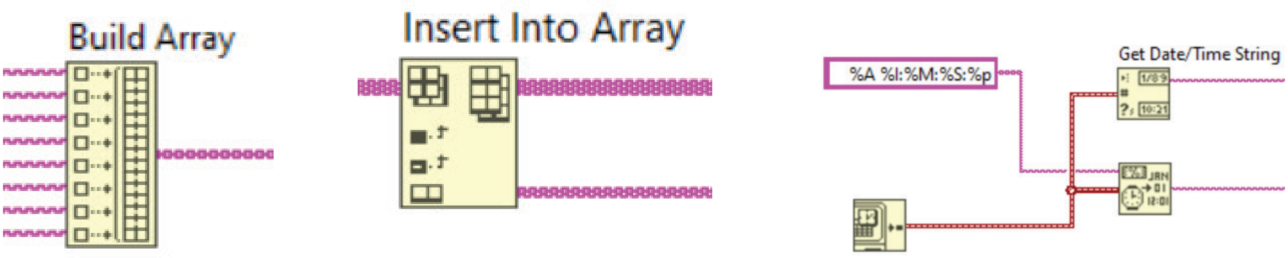


Figure 5. Numeric comparator.

Figure 5 shows a numeric comparator component. This component also functions like an operator that is used to compare the numeric values in the given program. This component helps in setting conditions or threshold values for the upper and lower bound of cut-off activation.

Figure 6(a) shows a Build Array component. Build Array creates an array from one or more elements or arrays. Build array is used to integrate multiple parameters such as flow in, flow out, time, date, current water level, cutoff activation, and so on into a single array and export the results to an Excel sheet. Figure 6(b) shows an Insert into Array component. The insert into array function inserts one or more elements or subarrays into an array. Figure 6(c) shows a Get Date/Time String component. This function enables to obtain the current time stamp for the dataset. Accurate date and time stamp will be of great help while training the machine with the acquired data values.



(a) (b) (c)

Figure 6. (a) Build array (b) Insert into array (c) Get date/time string.

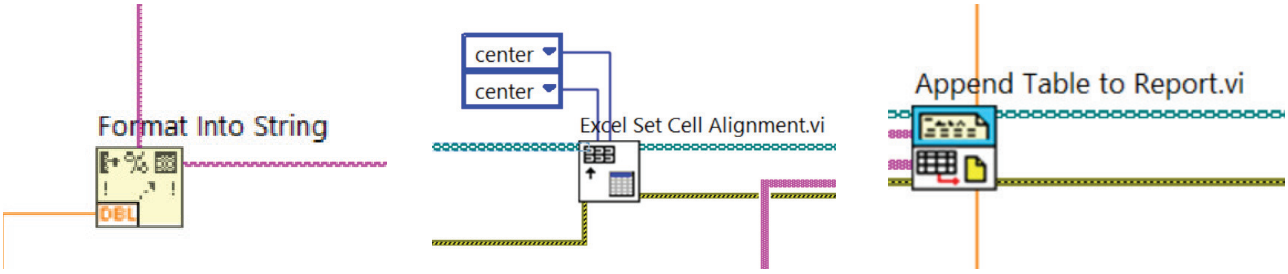


Figure 7. (a) Format to String (b) Excel Set Cell Alignment (c) Append Table to Report.

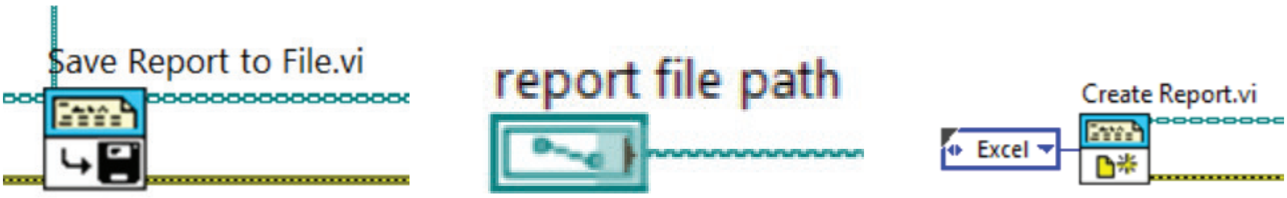


Figure 8. (a) Save Report to File (b) Report File Path (c) Create Report.

Figure 7 (a) shows Format to String component of LabVIEW. The Format to String describes how the function should convert the input parameters into the resulting string. Figure 7 (b) shows an Excel Set Cell Alignment component. Excel Set Cell Format VI takes in a reference to the report and sets format for the cells, based on the input given to the number format terminal. Figure 7 (c) shows an Append Table to Report component. This function enables to add rows and columns in the report.

Figure 8 (a) shows Save Report to File component. This is used to save report to excel sheet and save it in local drive. Figure 8 (b) shows a Report File Path component. It is used to give the path to the file to store it in local storage. Figure 8 (c) shows a Create Report component of LabVIEW. Create report function is used to create a excel report.

MACHINE LEARNING AND REGRESSION ANALYSIS

Developing an efficient water monitoring and management system requires the use of advanced predictive models to ensure accurate predictions of water supply availability and recharge times. In the initial stages of this research, examined various machine learning models to determine the most appropriate approach to analyzing data obtained from LabVIEW simulations [10].

Initial Model: Prophet

The Prophet model was initially selected due to its effectiveness in time series forecasting. Facebook created Prophet, a powerful forecasting tool that can handle daily observations of time series data with potential seasonal effects, holiday patterns, and other temporal structures. The system is designed to handle huge amounts of data to predict precise projections using LabVIEW data for training to train the system. Prophet, has particular way of functing and difficult to customize as per the requirements of this project. Due to this use of Prophet is inappropriate for the changing needs which is a main focus of this study.

Transition to Arima

To accomplished the requirement of changing demands the ARIMA (AutoRegressive Integrated Moving Average) model is used. ARIMA is useful and effective in time series forecasting and it has capacity to handle non-stationary data by differencing to make it stationary. This model demonstrated high accuracy in predicting values and interpolating missing data points. But, ARIMA model requires a large dataset to minimize errors and improve prediction accuracy [11-15].

Adoption of Linear Regression

Due to the limitations of Prophet and ARIMA, decided to use linear regression. This is simple and powerful machine learning model to fits the available dataset properly. In this models the linear relationship between a dependent variable (target) and one or more independent variables (features) is established. The linear regression is more simple and effective than Prophet and ARIMA models.

Mathematical Representation of Linear Regression:

The fundamental equation of Linear Regression [16, 17] is represented as:

$$Y = mX + C \tag{1}$$

Where,

Y is the dependent variable and it can be available Hours of Water Supply or Tank Refill Duration.

X is the independent variable and it can be current water level, flow in rate, flow out rate.

m is the slope of the line and represent the relationship between the dependent and independent variables.

C is the y-intercept and represent the value of y when x is zero.

Cost Function

The performance of the Linear Regression model is evaluated using the Cost Function, specifically Mean Squared Error (MSE). The average squared difference between the actual and predicted values is given by Cost Function, which help to quantify the model accuracy [18-20].

Mean Squared Error is given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - (mX_i + c)\right)^2 \tag{2}$$

Where,

N represent number of data points.

Y_i represent actual value of the dependent variable for the i-th data point.

X_i represent the value of the independent variable for the i-th data point.

m and *c* represent slope and intercept of the model respectiviely.

Linear Regression is used to find the values of m and c which helps to minimize the Mean Square Error. It helps to reduce the gap between predicted and observed values. Deep Learning can be used in latest water level implementation techniques for effective implementation [21, 22].

Implementation of Water Management System

The dataset generated by LabVIEW is used to trained The Linear Regression model and use to predict two critical parameters:

A. **Available Hours of Water Supply:** Equation 3 is used for predicting the number of hours the current water level will last based on the flow out rate.
B. **Tank Refill Duration:** Equation 4 is used for predicting the time required to refill the tank to its full capacity based on the flow in rate and the current water level.

These predictive capabilities into the water management system help, the model to provides real-time insights, enabling proactive management of water resources. This approach helps to minimizes water wastage and also ensures a consistent and reliable water supply.

DEVELOPED SYSTEM

The system works as follows:

i. Flow rate controllers set the flow in and flow out rates. The flow out rate from the underground tank is always equal to the flow in rate of the overhead tank.
ii. Depending on the flow rates, the water level in the tank increases or decreases. The current water level is displayed on an indicator in the front panel.
iii. If the current water level falls below a predefined threshold, the lower indicator turns red; otherwise, it remains green.
iv. The system calculates the projected available hours of water supply based on flow rates and the current water level.
v. Users can inquire about the estimated tank refill duration for the tank to be full based on the current water level.
vi. Mathematical formulae used for the forecasting of Available Hours of water supply and Tank refill duration are as follows:

$$\text{Available Hours of Water Supply (hrs)} = \frac{\text{Current water level(l)(height from bottom)}}{\text{Flow out rate}(\frac{l}{s})} \text{ x } \frac{1}{3600} \tag{3}$$

In equation 3 the parameters used are as follow.

A. **Current Water Level (l):** This parameter shows how much water is in the tank right now, expressed in litres. It is important because it establishes how much water is still usable.
B. **Flow Out Rate (l/s):** This indicates, how quickly water is being used up or drained from the tank, in litres/second.
C. **Conversion Factor (1/3600):** This factor is used to converts the time hours from second.

By using Equation 3 the number of hours the water supply will last based on the current water level and the rate at which water is being used is calculated. For example, if the tank has 10,000 litres of water and the flow out rate is 2 litres per second, the calculation helps in determining how long the water will last before the tank is empty. This information is important for managing water usage and during periods of shortage.

$$\text{Tank Refill Duration (hrs)} = \frac{\text{Total height of tank(l)} - \text{current water level (l)}}{\text{Flow in rate}(\frac{l}{s})} \text{ x } \frac{1}{3600} \tag{4}$$

Equation 4 can be used to calculate the time required to fill a tank from its current level to its maximum capacity. For example, if a tank has a capacity of 5,000 liters and currently holds 1,000 liters at a flow rate of 3 liters per second, this formula will help determine time required to fill the remaining 4000 liters in the tank. This estimation is required to plan activity of filling and stoping water for refilling and avoiding overflow of tank respectively.

vii. Readings of flow in rate, flow out rate, current water level, available hours of water supply, and tank refilled

Date	Time	flow out rate (l/s)	Flow in rate (l/s)	Current water level(l)	Cutoff_Activation	Avail_hrs_of_water_supply	Time required to fill the tank(hrs)
30-10-2023	Monday 11:41:37:AM	0	2.12	0	1	0	1.31
30-10-2023	Monday 11:41:38:AM	0	2.12	2.12	1	0	1.31
30-10-2023	Monday 11:41:39:AM	0	2.12	4.24	1	0	1.31
30-10-2023	Monday 11:41:40:AM	0	2.12	6.36	1	0	1.31
30-10-2023	Monday 11:41:41:AM	0	2.12	8.47	1	0	1.31
30-10-2023	Monday 11:41:42:AM	0	2.12	10.59	1	0	1.31
30-10-2023	Monday 11:41:43:AM	0	2.12	12.71	1	0	1.31
30-10-2023	Monday 11:41:44:AM	0	2.12	14.83	1	0	1.31
30-10-2023	Monday 11:41:45:AM	0	2.12	16.95	1	0	1.31
30-10-2023	Monday 11:41:46:AM	0	2.12	19.07	1	0	1.31
30-10-2023	Monday 11:41:47:AM	0	2.12	21.19	1	0	1.31
30-10-2023	Monday 11:41:48:AM	0	2.12	23.31	1	0	1.31
30-10-2023	Monday 11:41:49:AM	0	2.12	25.42	1	0	1.31
30-10-2023	Monday 11:41:50:AM	0	2.12	27.54	1	0	1.31
30-10-2023	Monday 11:41:51:AM	0	2.12	29.66	1	0	1.31

Figure 9. Dataset obtained from LabVIEW simulation.

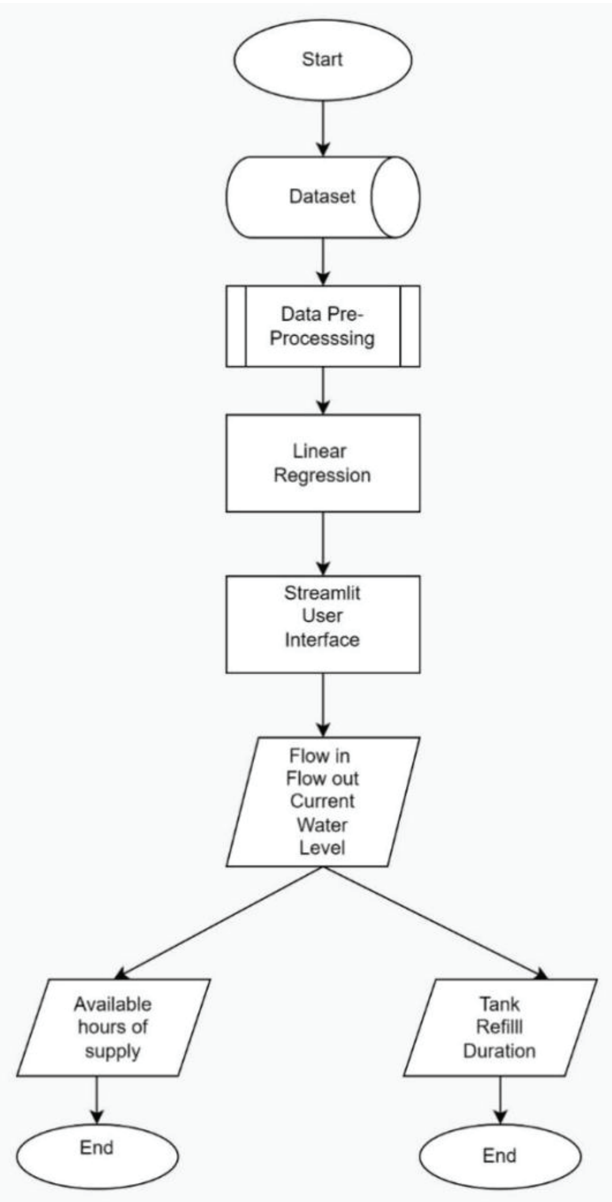


Figure 10. Flow chart of machine learning algorithm (linear Regression).

time, are continuously logged and shown in Figure 9 for obtained data set.

viii. The logged data is transferred to Excel sheets at regular intervals, creating a comprehensive dataset. Sample dataset is as follows:

ix. The dataset serves as training data for a machine learning model, particularly using the linear regression algorithm as shown in figure 10.

x. The trained model predicts values such as Available Hours of Water Supply and Tank Refill Duration based on new input data.

xi. The generated predictions, along with other readings, are logged back into Excel sheets for generating record of daily or weekly patterns.

This process forms a closed loop, continually updating and refining predictions based on real-time data and historical patterns.

RESULTS AND DISCUSSION

A graph is generated that correlates water, volume and time using LabVIEW. This graph helps to predict water consumption patterns by identifying peak periods, facilitating improved resource planning, and forecasting future water availability most effective way. Figure 11 shows a line graph that depicts the trend of Current water level (l) for different Timestamp.

Figures 11 and 12 illustrates fluctuatations in the water levels of underground and overhead tanks for different time. This helps to provide information about usage patterns and identifying peak periods of water requirement.

Thus, Figure 13 and 14 helps to analyze the efficiency of the water flow control system and how the system manages the balance between water inflow and outflow. Initially, a certain water flow-in rate and flow-out rate is provided to the underground tank. Once the underground tank is full, the flow-in rate is reduced to nearly zero with the constant flow-out rate. Since the system is developed such that the water flow-out rate from the underground tank becomes the flow-in rate for the water flowing in the overhead tank,

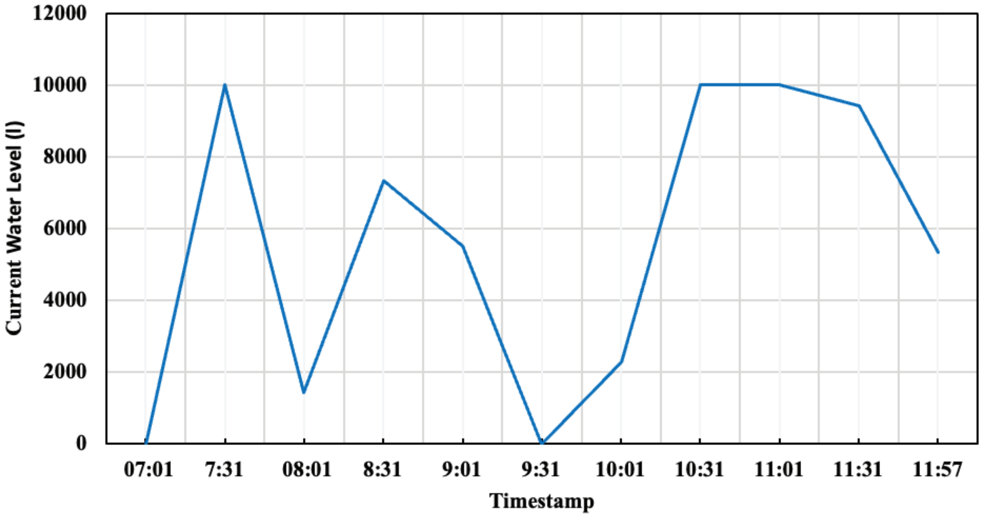


Figure 11. Current water level (liters) in underground tank for different timestamps on tuesday evening.

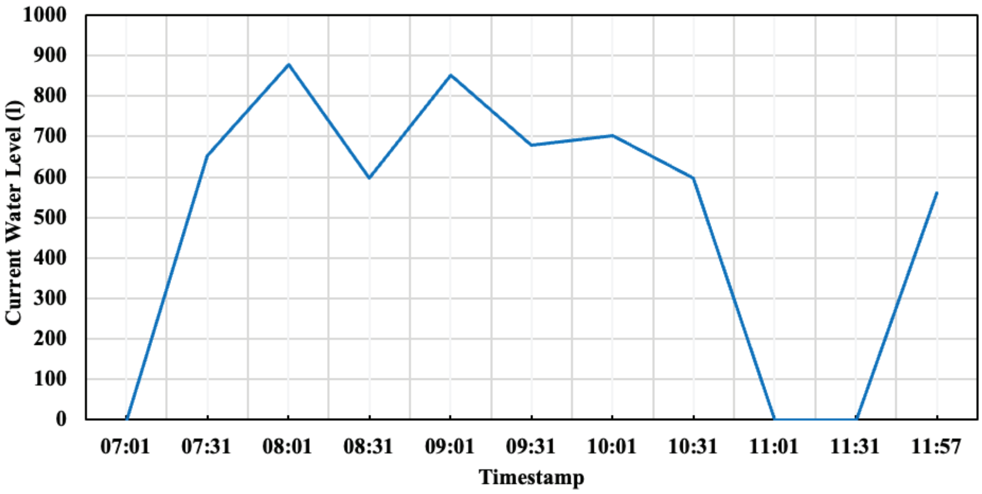


Figure 12. Current water level (liters) in overhead tank for different timestamp on tuesday evening.

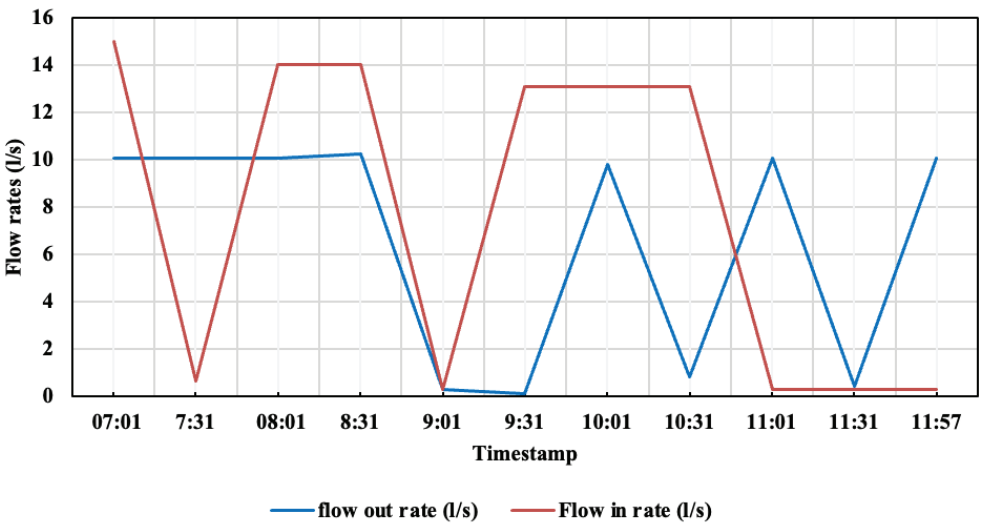


Figure 13. Flow-in and flow-out rates for underground tank for different timestamp on tuesday evening.

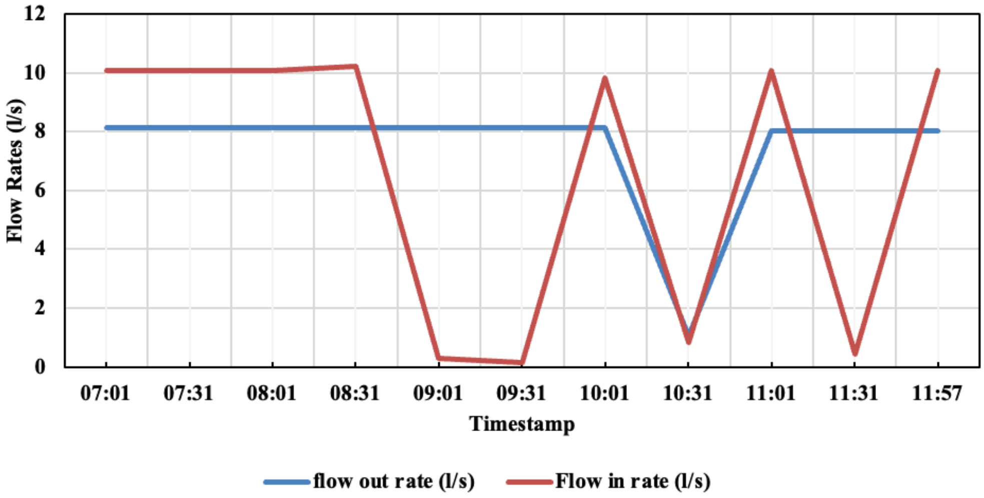


Figure 14. Flow-in and flow-out rates for overhead tank for different timestamp on tuesday evening.

there is a peak in the flow-in rates of the overhead tank in the Fig. 14 at the point at which the flow-out rates for the underground tank in the Fig. 13 is incremented. The flow-out rate of the underground tank is kept at a constant fluctuating rate between nearing 0 and 10.03 l/s considering that water will be pulled out of the tank with the help of a motor and thus will remain constant. The flow-out rate for the overhead tank is kept at constant keeping in mind that water flows out from the overhead tank with the help of gravity and thus, will remain constant all the time.

Figure 15 and 16 helps with water distribution schedule planning and prediction by showing the change in water supply hours over time. In Fig. 15, the trend of the available hours of water supply is similar to that of current water level as the more the water level, the more is the available hours of water supply. It highly depends on the current water level and the flow-out rate of the respective tank. Figure 16 also shows a similar trend.

Figure 17 and 18 illustrates how long it takes to refill the tanks and provides information on how well the system works to restore water levels. At a given instant of time, for the underground tank, the flow-in and flow-out rates both are provided leading to the depiction of the above mentioned line graph. In this graph, the tank refill duration is highly dependent on the current water level and the flow-in rate of the respective tanks. Line graphs are chosen for their suitability in depicting continuous variation over time. These graphs offer a thorough understanding of the operation of the water supply system, supporting measures for conservation and improvement.

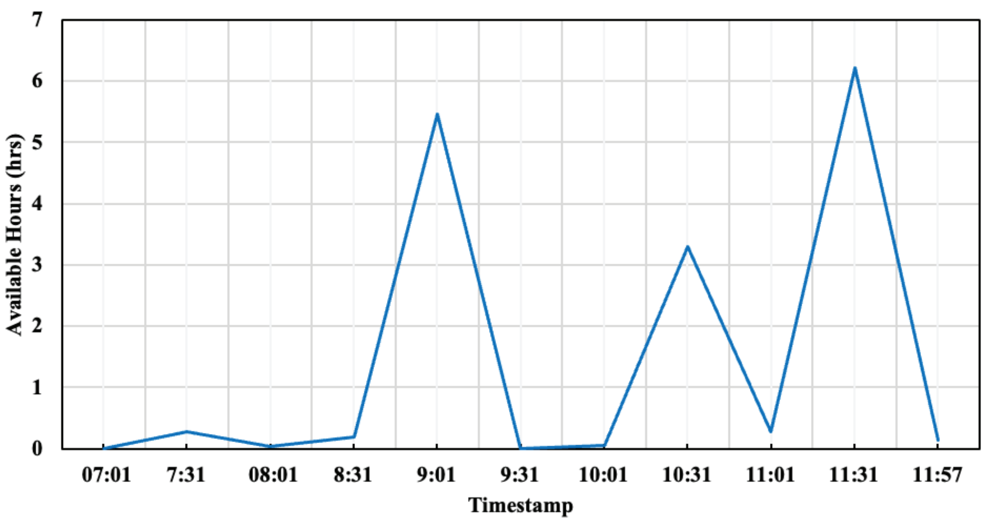


Figure 15. Available hours of supply (hrs) for different timestamp in underground tank on tuesday evening.

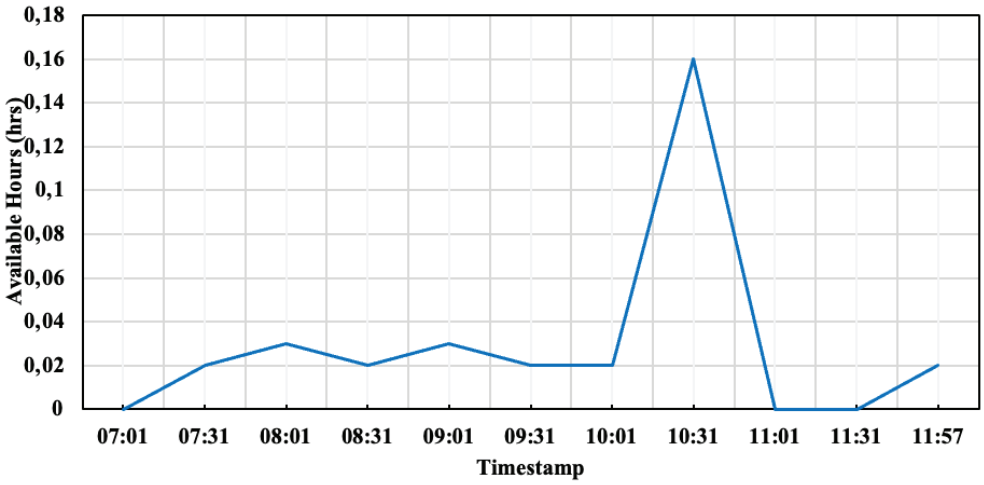


Figure 16. Available hours of supply (hrs) for different timestamp in overhead tank on tuesday evening.

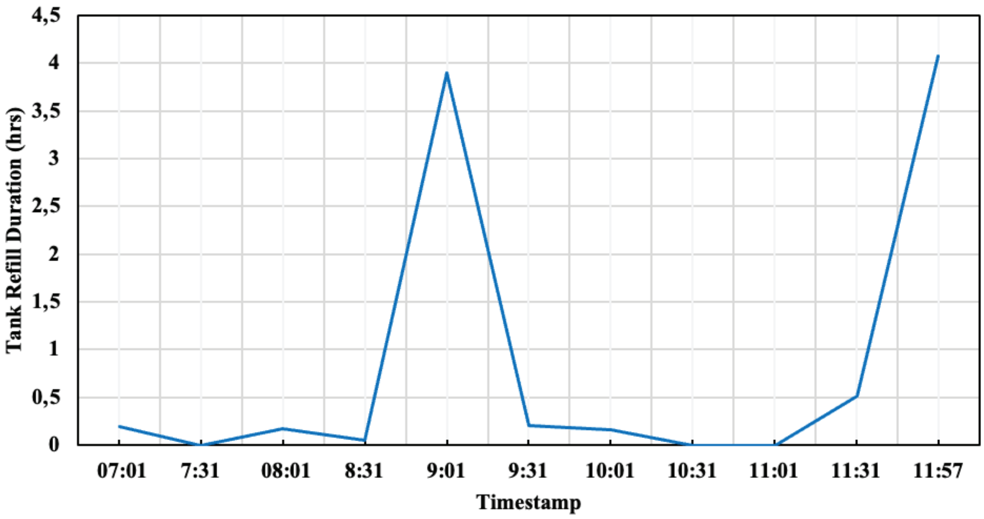


Figure 17. Tank Refill Duration (hrs) of underground tank for different timestamp on tuesday evening.

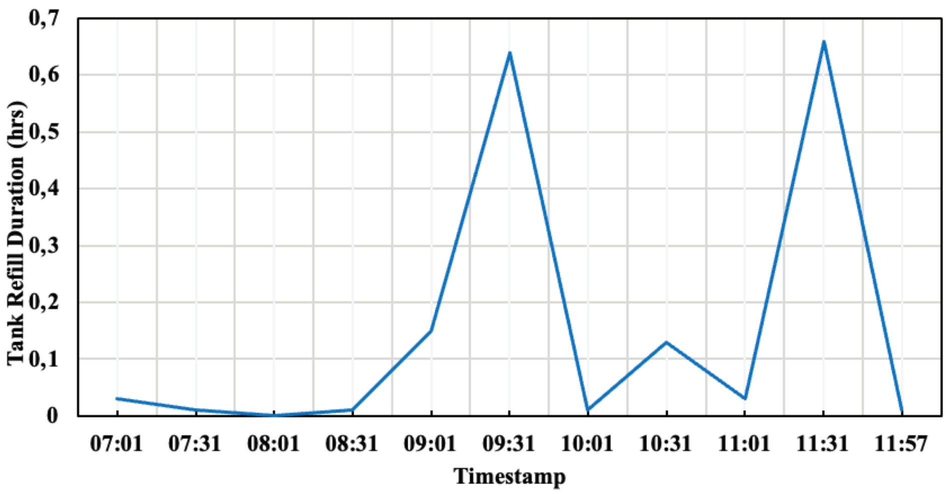


Figure 18. Tank refill duration (hrs) of overhead tank for different timestamps on tuesday evening.

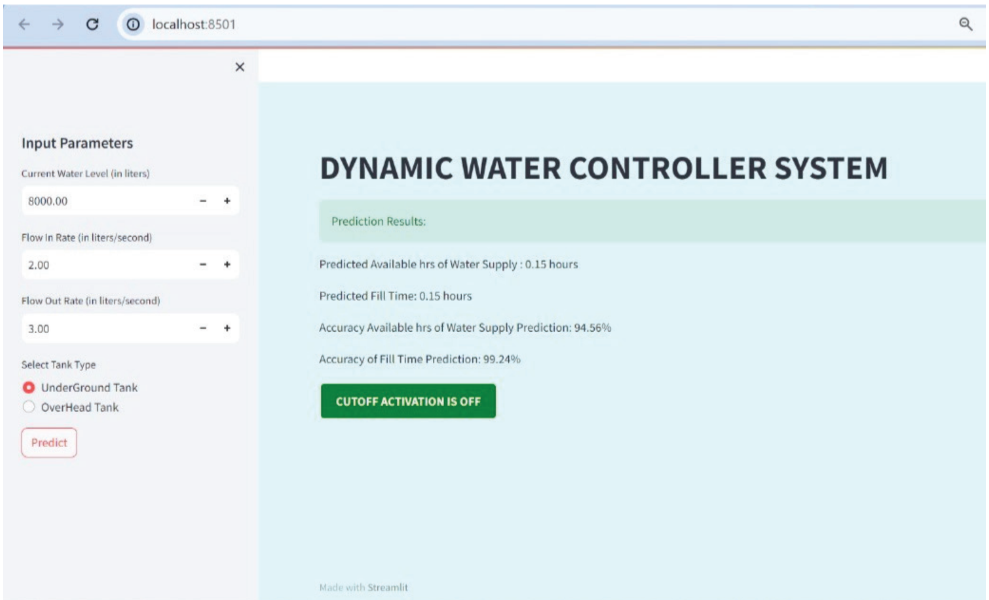


Figure 19. User interface for decision making.

The linear regression model was trained from the dataset obtained from LabVIEW. After that, a User Interface using streamlit was generated as shown in figure 18, which takes flow in, flow out rate, and current water level as input. Streamlit is an open-source Python Library that allows you to create web applications in an efficient manner for Machine Learning and Data Science projects. It allows you to visualize the data and also make the system more user friendly with its simple and easy user interface. It can be generated easily using familiar python syntax and scripts. With the provided inputs from LabVIEW and by using linear regression it will predict Available hours of water supply and Tank refill duration which will further help us to efficiently control water usage and save water from being wasted.

With the help of the obtained Dataset, the LabVIEW and Machine Learning results were analyzed. It was found that LabVIEW estimated values and Machine Learning predicted values are very close.

i. **Dependence on Accurate Data Simulation:** The LabVIEW-simulated data is significantly used for developing the model. Though LabVIEW offers a robust structure for developing realistic datasets, it may affect accuracy of prediction in actual circumstances. The forecasts accuracy is depends on any differences between the simulated and real situations data sets.

ii. **Limited Size of Dataset:** - Large size datasets are required to enhanced machine learning model performance, particularly for regression analysis models. In spite of extensive, the dataset created by LabVIEW for this project may be have limitations. This may have restriction on the model's capacity to generalize and make correct predictions in a different scenario. For limited data set Linear Regression is the best option compare to sophisticated models like PROPHET and ARIMA.

iii. **Real-time Data Integration:** - The machine learning models is trained by data produced by LabVIEW. While integrating real-time data from actual water management systems, technical difficulties could arise such as data transfer delay, contineous updatation, and possible differences between real-time and historical data. It implies that certain hardware and software setups are required when using LabVIEW as the main tool for data production for training model. The developd system's capacity to scale and adapt to other contexts or systems that do not support LabVIEW may be limited by this dependence.

iv. **External and Environmental Factors:** The developed system's prediction algorithms may not consider all other factors that could affect water levels and flow rates, like variations in weather patterns, user habits, or unforeseen interruptions to the water supply. This may increase uncertainty and decrease prediction accuracy.

v. **Simplified Assumptions**: In this dynamics system, assumptions, serve as the foundation for the mathematical formulas used to predict the number of hours available for water delivery and the time needed to refill the tank. In Real-world water systems different tank designs, pressure variations, and sporadic supply disruptions will might behave more complicatedly.

vi. **Maintenance and Calibration:** Regular maintenance, calibration of sensors and other hardware components are required for the system to sustain its accuracy over time. Any maintenance gaps will result in inaccurate data collection, which would affect the accuracy of the system's forecasts.

vii. **Requirement for User Expertise:** - To maintain this developed system, certain amount of expertise with both LabVIEW and machine learning is required. Users without prior experience in these fields may find this requirement difficult which could restrict the system's usability and accessibility.

viii. **Problems with Scalability:** - The developed model is a scale down model, there may be difficulties when trying to integrate it with other tanks and distribution systems or scale it up to handle larger water networks. For accurate implementation, more complex data management, and the requirement for more advanced prediction models are some of these problems.

CONCLUSION

The developed Dynamic Water Management System, which integrates LabVIEW for dataset collection, a Linear Regression model for forecasting, and a user-friendly interface for real-time interaction, offers an efficient solution for water resource management. LabVIEW is an excellent platform for accurate data collection, while machine learning ensures accuracy in prediction of time requirement to tank refill duration. The intuitive user interface allows easy input of critical parameters such as flow-in, flow-out, and current water level, making the system accessible to various users. An accuracy of 94.56% and 99.24% for predicting Available Hours of Water Supply and Tank Refill Duration respectively using Linear Regression Machine Learning model. For implementing with actual sensors for flow rate and water level detection will enable real-time data acquisition, leading to a dynamic and efficient automated water control system utilizing IoT. This integration highlights the system's scalability and adaptability for larger applications like municipal water systems and large-scale industrial use. The use of machine learning for predictive analytics highlights data-driven decision-making in water management, motivating further research into advanced models. Additionally, optimizing water usage and minimizing waste contributes to sustainable resource management, addressing global environmental challenges. The Dynamic Water Management System satisfies current water management needs and also establishes a new benchmark for intelligent, efficient, and sustainable practices, paving the way for future research and development.

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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