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WatAI: AI-Based System for Real-Time Flow Monitoring and Demand Prediction in Water Networks

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Abstract

Efficient monitoring and control of water demand are crucial for sustainable water resource management. Bogotá, Colombia, currently faces supply rationing due to climate change and ineffective public policies. This study presents *WatAI* (Water + AI), an AI-powered system designed for real-time flow monitoring and demand prediction in water distribution networks. The system integrates flow sensors, microcontrollers, and machine learning algorithms to capture high-resolution temporal data. A dynamic sequential artificial neural network (ANN) with ReLU activation and Adam optimization is implemented, allowing real-time adjustments (1 sec) to flow variations and anomaly detection. To enhance accuracy, the system applies real-time signal filtering and transmits early alerts via email to service providers. The ANN model achieved an MSE of 0.006510, demonstrating improved accuracy with increasing historical data. Compared to traditional forecasting models, *WatAI* provides higher temporal resolution and adaptability to demand fluctuations, making it a more effective tool for intelligent water management. The study contributes to the development of IoT-based smart infrastructures for sustainable urban water planning.

Keywords: Artificial Neural Networks; Flow Prediction; IoT; Machine Learning; Real-time Monitoring; Smart Water Management.

1. Introduction

Efficient water resource monitoring is critical for the development of smart cities, especially in high-density urban areas like Bogotá. Population growth and climate variability are putting pressure on water supply systems, requiring advanced technological solutions to optimize resource allocation, decision-making, and reduce operating costs. In this context, the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) has emerged as a transformative approach to improving real-time flow prediction in water distribution networks. The ability to anticipate variations in consumption allows utilities to take proactive measures, ensuring efficient water distribution and infrastructure resilience.

Several studies have demonstrated the effectiveness of AI-based solutions in water management. Mounce et al. [1], utilized machine learning techniques to detect anomalies in flow and pressure by increasing sampling frequencies in water networks. Similarly, Samikwa et al. [2] developed an IoT-based ANN model for real-time flood prediction, integrating edge computing and precipitation sensors to enhance forecasting accuracy in low-power systems.

Furthermore, Adeleke et al. [3] introduced a hybrid IoT system combining Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for real-time water quality monitoring, achieving high accuracy in impurity level detection. The development of intelligent systems is essential for the conservation of water resources and the implementation of contingency plans for atypical events, such as floods, strengthening early warning systems and

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mitigating their environmental and economic impacts. Bhati et al. [4] consider a low-cost IoT system to monitor water quality in real-time, the authors employ machine learning algorithms such as Naïve Bayes and Decision Tree. Their application in rural communities improved the detection of contamination and the prevention of diseases caused by contaminated water, demonstrating the impact of AI in water management. The synergy between artificial intelligence and IoT makes it possible to decipher hidden patterns in water systems, which opens the possibility of implementing strategies to optimize resource management. As these patterns are understood, sustainable and non-intrusive measures can be adopted that reduce environmental impact and improve efficiency in decision-making. In the field of efficient water management, automation has proven to be a fundamental tool for optimizing water use.

An example of this is the fuzzy rule-based automatic irrigation controller based on fuzzy rules and IoT, developed by Poyen et al. [5]. This system improves irrigation efficiency through wireless sensors, achieving a 27% reduction in water consumption and a 40% increase in crop yields, demonstrating the positive impact of automation in water management. In water leak detection, the combination of IoT and machine learning has enabled the development of more efficient, real-time solutions. Islam et al. [6] proposed a low-power ML-based (Machine Learning-based) IoT device to detect leaks using acoustic sensors and RF data transmission. Their optimized model achieved an accuracy of 98.96%, reducing the impact of water losses in the urban environment. Similarly, in terms of leak detection in water networks, the integration of IoT with advanced artificial intelligence models has improved the accuracy and efficiency of monitoring. An example of this is the system based on BiLSTM (Bidirectional Long Short-Term Memory) and Monte Carlo Dropout, which uses pressure and flow sensors to process data in real-time using Kalman filtering and spectral analysis. This approach achieved an accuracy of 87.48 % in training and 80.48 % in validation, enabling early identification of leaks and optimizing water management [7]. Indeed, in the optimization of water distribution networks, accurate demand prediction leads to the minimization of losses in the water system. A model based on IoT and deep learning compared LSTM models with ARIMA (Autoregressive Integrated Moving Average) to estimate consumption more accurately, integrating this prediction into a smart water system.

The implementation of this distribution network made it possible to reduce losses during transport and to guarantee the quality of the water supplied [8]. On the other hand, in water level prediction, the integration of IoT with neural networks improves the response to extreme events. A decentralized system based on sensors with edge computing and ANN models was able to forecast water levels three hours in advance, optimizing decision-making, which significantly reduced the probability of flooding in the sector [9]. In addition, a system based on flowmeters and predictive models in the cloud compared neural networks with ARMA (Autoregressive Moving Average) and SARMA (Seasonal Autoregressive Moving Average) models, achieving lower errors in the estimation of the population's monthly consumption. The development is connected through a mobile application for real-time data monitoring and analysis [10].

Despite significant advancements in AI-based water management, existing models remain predominantly static, limiting their adaptability to real-time demand fluctuations. To address this, *WatAI* integrates DNN (Dynamic Neural Networks) that continuously updates its predictions, enhancing its ability to adjust to changing conditions. Furthermore, while most research has focused on water quality monitoring or leak detection, there is a notable gap in real-time demand forecasting. *WatAI* prioritizes demand prediction to optimize distribution efficiency, ensuring a more balanced and responsive water supply system. Additionally, current models often lack high-resolution anomaly detection techniques, reducing their effectiveness in distinguishing genuine demand variations from irregularities. To improve precision, *WatAI* incorporates multi-layer filtering methods, including low-pass, high-pass, and moving average filters, to refine anomaly detection and minimize false alerts.

Therefore, efficient water management represents a challenge for large cities such as Bogotá. Current distribution systems have limitations in predicting consumption and early detection of anomalies due to their low temporal resolution, minimal instrumentation and lack of adoption of intelligent algorithms that optimize real-time decision-making. Consequently, the synergy between artificial intelligence, IoT, and dynamic prediction models is proposed as an innovative solution. *WatAI* is developed as a system capable of improving the accuracy of flow prediction in water distribution networks, providing real-time information and generating alerts in the event of sudden changes in demand. The main objective of this study is the development and implementation of *WatAI*, an IoT prototype based on DNN for real-time flow prediction in water distribution networks. Finally, the contribution of this study focuses on the integration of dynamic neural networks with IoT sensors to improve real-time water consumption prediction. Unlike previous approaches using static models, *WatAI* implements a flexible architecture with continuous learning, optimizing decision-making in water distribution systems.

Thus, the article is structured as follows. Section 2 describes the methodology, detailing the design of the *WatAI* system, the sensor configuration, the architecture of the artificial neural network, and the real-time data processing techniques. Section 3 presents the results, including the system's predictive performance, model evaluation metrics, and comparisons with traditional forecasting approaches. Section 4 provides a discussion, analyzing the implications of the findings, comparing the proposed system with existing models, and identifying potential areas for improvement. Finally, Section 5 presents the conclusions, summarizing the key contributions of the study and suggesting future research directions to enhance the predictive capabilities of intelligent water management systems.

1.1. Technical Specifications of the WatAI Prototype

WatAI integrates flow sensors, microcontrollers, and machine learning algorithms to detect consumption patterns in distribution networks. It uses a sequential DNN with ReLU (Rectified Linear Unit) activation and Adam (Adaptive Moment Estimation) optimization, adjusting predictions at one-second intervals to improve anomaly detection and generate early warnings. The results show a reduction in MSE (Mean Squared Error) as the data history increases. Figure 1 illustrates different phases of implementation: on the left, tests in the hydraulics laboratory of the Universidad Distrital Francisco José de Caldas; on the top right, the assembled prototype; and on the bottom right, its installation in a water supply network. *WatAI* demonstrates its effectiveness in real-time monitoring, optimizing water resource management and facilitating decision-making in water distribution.

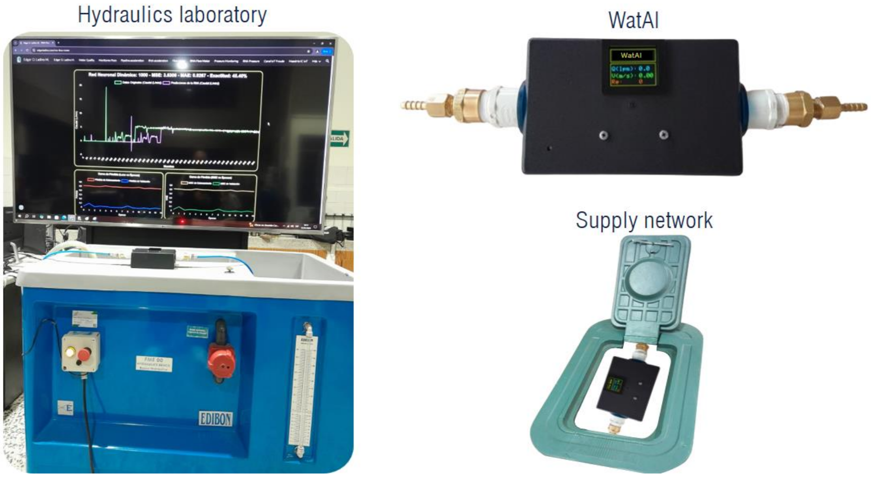

Figure 1. Implementation and testing of the WatAI prototype. Laboratory and field testing of the prototype

In order to make the system independent of commercial software downloads, an HTML (HyperText Markup Language) platform was developed for real-time web-based queries. Thus, HTML web platforms allow real-time queries of water quality, minimizing human intervention and optimizing data management [11]. The generated web services display the statistics of flow rate, flow velocity and Reynolds number. The signal is filtered in real-time, identifying the type of noise present in the time series. In terms of prediction, the web page displays the data history and the real-time predictions obtained from the sequential neural network.

1.2. Technical Specifications of the WatAI Prototype

The *WatAI* prototype is an integrated system for real-time flow monitoring. It uses an ESP8266 microcontroller for data acquisition, processing and wireless transmission. The system includes a YF-S201 flow meter, which produces a digital pulse signal proportional to the water flow, with a ratio of approximately 7.5 pulses per liter. The sensor was calibrated in the lab and then connected to the D4 GPIO (General Purpose Input/Output) of the ESP8266. The prototype incorporates a 1.8-inch OLED (Organic Light-Emitting Diode) display (128×160 pixels) for real-time display of captured data. For event notification, it integrates an RGB (Red Green Blue) module, which emits visual alerts according to predefined flow rate thresholds. The system is powered by a 5,000 mAh battery, which offers a battery life of up to 72 hours, with the option of direct connection to a 110 V supply for continuous operation. Figure 2 shows the architecture of the electronic system.

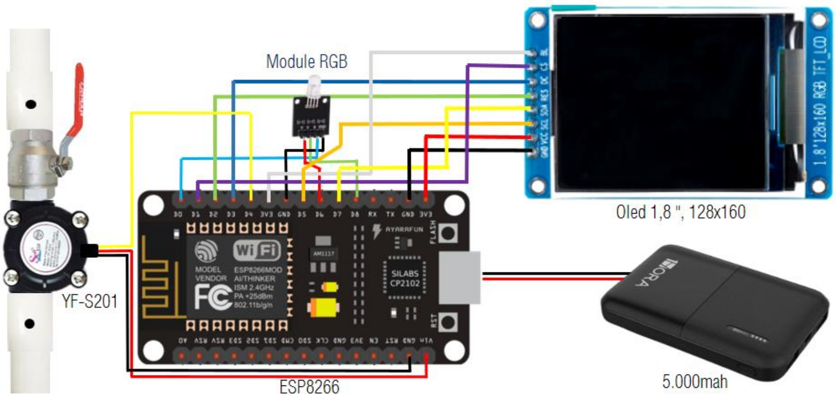

Figure 2. WatAI Electronic architecture. System composed of an ESP8266, a YF-S201 sensor

In the programming of the ESP8266 microcontroller, the libraries necessary for the development of the model were configured. This included ESP8266WiFi.h for wireless connectivity, SPI.h and Wire.h for communication with peripherals, Adafruit_GFX.h and Adafruit_ST7735.h for OLED display control, and ESP8266HTTPClient.h along with WiFiClientSecure.h for sending email notifications. The ST7735 OLED display is initialized via SPI communication, using pins D1 (CS), D2 (RST) and D3 (DC). The YF-S201 flow sensor is connected to GPIO D4, configured as an interrupt input to capture the pulses produced by the water flow. For visual signaling, the RGB module uses pins D6 (red), D8 (green) and D0 (blue), allowing alerts to be triggered based on the recorded flow rate values. This scheme is in line with the approach proposed by Yang et al. (2022) for pipeline leak detection using NPW (Negative Pressure Wave) and artificial intelligence.

2. Methods

2.1. Flow Monitoring System Design

Sensor calibration is a fundamental process for establishing an accurate correlation between the input variable (sensor signal) and the output variable (actual volumetric flow rate). In this study, the YF-S201 sensor was calibrated using an experimental procedure based on direct measurements with a standard instrument. To do this, a graduated cylinder was placed under the fluid outlet, in which the volume of water was collected over a predefined time interval, controlled by a high-precision stopwatch. The volumetric flow rate was then calculated by dividing the accumulated water volume by the collection time, thus obtaining reference values for sensor calibration. Figure 3 shows the calibration curve obtained for the YF-S201 sensor, in which the experimentally measured flow rates were plotted against the values reported by the sensor. It can be seen that the data follow a fit of the form $y = 0.84x^{1.0817}$, with a coefficient of determination $R^2 = 0.9915$. This indicates a high correlation between both measurements. This adjustment allows for the establishment of a calibration equation that corrects the sensor values, improving its accuracy in real-time flow measurement. The equation was inserted into the Arduino code. The calibration procedure based on volumetric measurements made it possible to determine the exact relationship between the sensor output signal and the actual flow rate, ensuring greater reliability in data acquisition. As a result, the *WatAI* system can make accurate flow estimates in the water distribution network, minimizing measurement errors and improving anomaly detection.

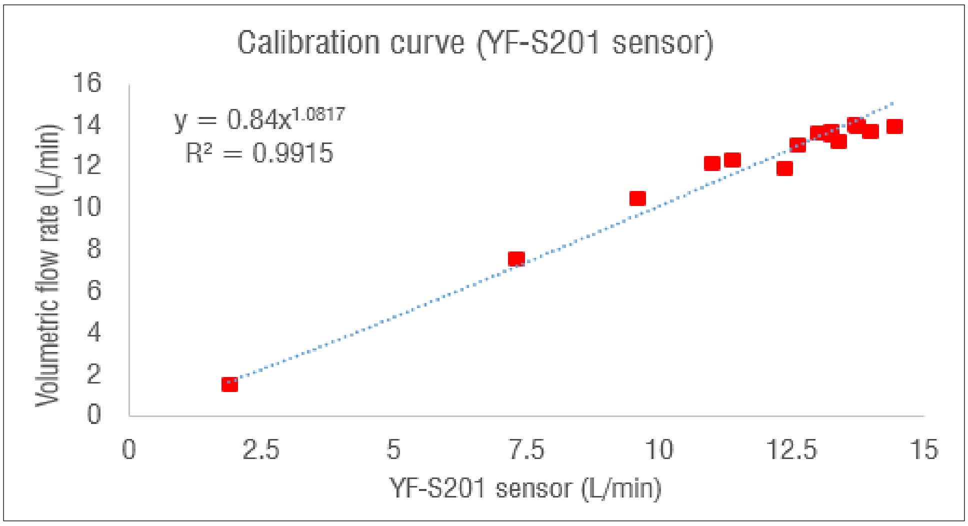

Figure 3. Calibration curve (YF-S201 sensor)

From the data obtained by the YF-S201 sensor, which generates a digital pulse signal proportional to the flow rate, advanced processing techniques are applied to estimate water demand in real-time. Each pulse corresponds to a specific liquid volume flowing through the sensor, where an internal blade rotation generates a ratio of 7.5 pulses per liter of water. To ensure accurate measurements, a calibration process is conducted to correct deviations and improve the reliability of the data. This information is then transmitted via Wi-Fi and stored on a MATLAB server using the ThingSpeak platform, enabling remote access and real-time analysis. To enhance signal accuracy and mitigate distortions, low-pass, high-pass, and moving average filters are implemented dynamically, ensuring precise flow estimation and robust data processing.

Figure 4 illustrates the integrated system for capturing and monitoring flow data in water distribution networks. The *WatAI* system continuously collects real-time data, wirelessly transmitting it to the cloud, where it is processed and graphically represented on an interactive monitoring platform. The integration of IoT technologies in water systems enhances efficiency by enabling utilities to detect consumption patterns, anomalies, and leaks, optimizing resource management [12]. The platform supports CSV and PDF export formats, facilitating historical analysis and report generation. Additionally, automated email alerts notify service providers of significant flow variations, allowing for timely intervention and improved system reliability.

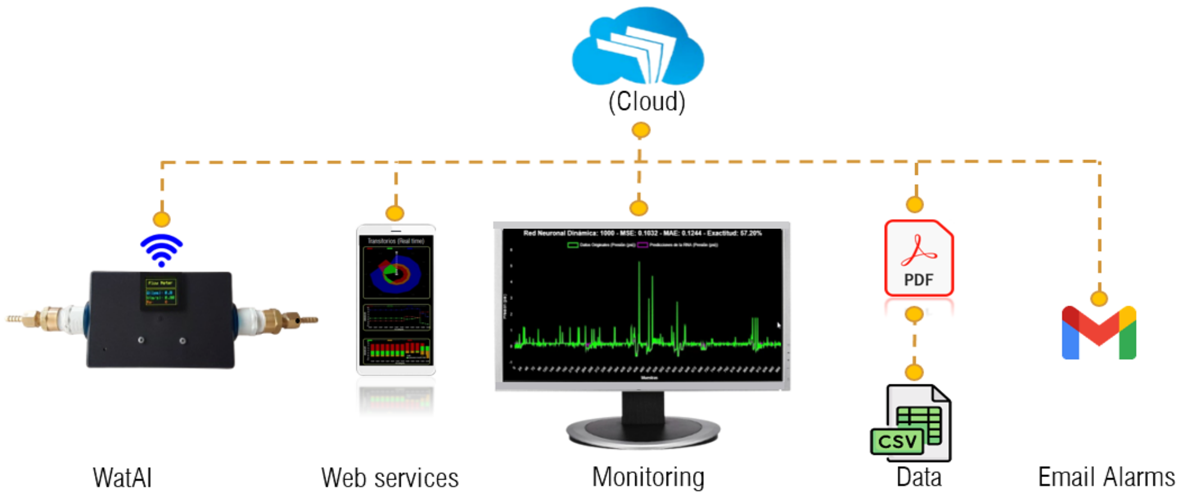

Figure 4. WatAI cloud-based system enables real-time flow monitoring, data storage, and anomaly detection

As depicted in Figure 5, the *WatAI* system begins with real-time data acquisition from the YF-S201 flow sensors, which detect flow fluctuations and transmit digital pulse signals to a microcontroller for preprocessing. This stage includes real-time noise filtration, ensuring high-fidelity measurements for subsequent flow prediction and anomaly detection. A DNN, optimized with ReLU activation and Adam optimization, processes the filtered data, predicting flow variations at one-second intervals. The DNN continuously refines its predictions using MSE minimization, improving detection accuracy over time. The results are displayed in a web-based dashboard, offering real-time visualization and analysis. This system represents a significant advancement over traditional static models, as it dynamically adapts to consumption trends and anomalies, contributing to intelligent water management and sustainable urban planning.

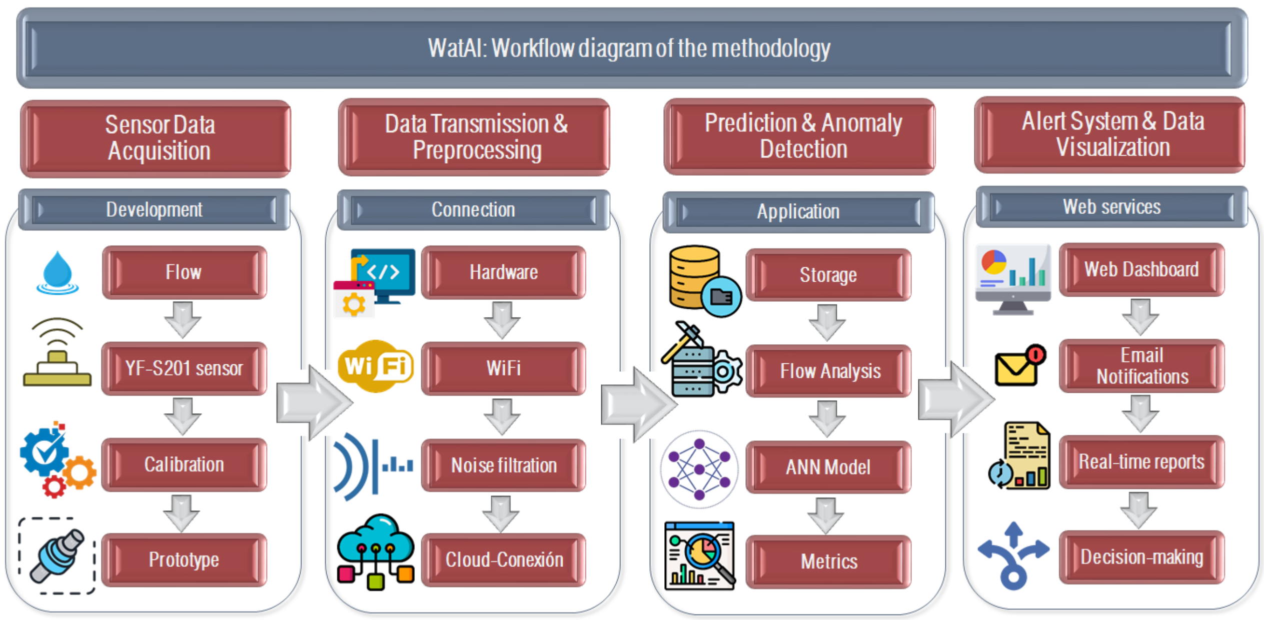

Figure 5. Workflow diagram

Once preprocessed, the data is transmitted via Wi-Fi to a cloud-based infrastructure, enabling real-time remote monitoring. A DNN, optimized with ReLU activation and Adam optimization, processes the flow data, predicting demand variations at one-second intervals. The DNN model continuously updates its predictions, adapting to fluctuations in consumption. To enhance its accuracy, performance metrics such as MSE and trend analysis are used, ensuring reliable detection of anomalies and sudden flow rate changes. The final stage of the *WatAI* methodology integrates data visualization and decision-making. A web dashboard displays real-time monitoring results, including flow rate, anomaly alerts, and historical trends. The system automatically generates email notifications to service providers when irregularities are detected, enabling rapid intervention. Additionally, the real-time reporting module supports decision-making by providing comprehensive analytics for water distribution network operators, facilitating proactive water management and supply optimization.

2.2. Data Visualization and Alerts

From the data sent by ThingSpeak and using the channel ID (Identifier or Identification) and the API Key (Application Programming Interface), an online dashboard was configured in HTML to visualize in real-time the behavior of the flow, the flow velocity and the Reynolds number. This last parameter allows determining whether the flow is laminar, unsteady, or turbulent, depending on its value. HTML development offers greater versatility and accessibility compared to platforms such as MATLAB, as the user does not need to download or install additional software, but simply access the IP address of the system. Figure 6 shows the dashboard developed for this study.

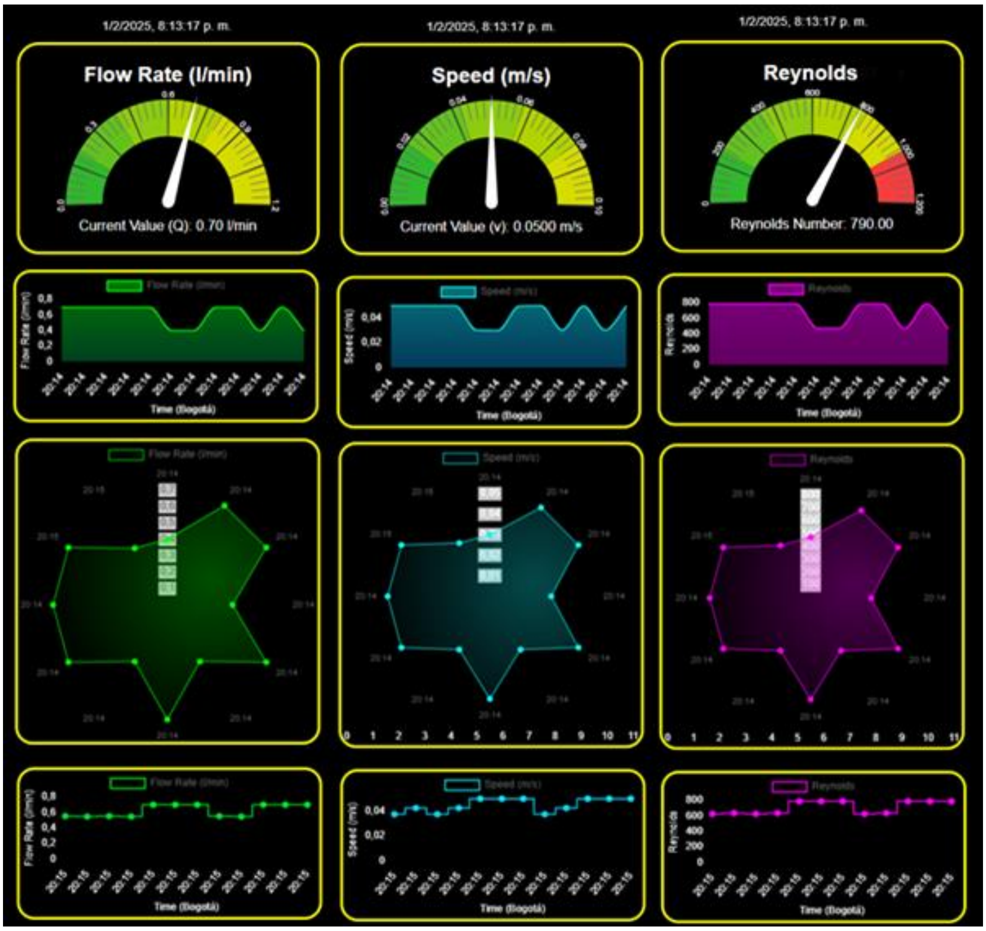

Figure 6. Real-time flow monitoring dashboard with gauges and bar graphs for analyzing flow rate

To ensure data quality, reliability, and sensor consistency over time in the dynamic environment of a water distribution network, the *WatAI* system employs a comprehensive, multi-layered approach, combining sensor calibration, advanced real-time signal processing, and continuous validation. It also implements dynamic filtering techniques, such as low-pass, high-pass, and moving average filters, to mitigate noise and eliminate transient fluctuations that could affect measurement accuracy. To compensate for long-term sensor drift and ensure stable measurements, the system runs periodic recalibration routines, complemented by self-test algorithms that compare current readings with historical trends, allowing deviations to be detected and potential measurement errors to be proactively corrected.

Similarly, from the flow rate, flow velocity and Reynolds number data, spectrograms are generated in real-time (every second) for each variable, with the aim of visualizing the frequency variation as a function of time. This allows behavioral patterns to be identified and possible anomalies in the system dynamics to be detected. The real-time spectrogram optimizes feature extraction in IoT, improving spectrum detection with less computational load [13]. FFT (Fast Fourier Transform) enhances real-time spectrum analysis, optimizing compression, recognition, and noise reduction in IoT and AI (Artificial Intelligence) [14]. The comparison of parameters allows evaluating the transition between laminar, unsteady and turbulent flow regimes according to the opening of the valve in the laboratory. In field tests, the spectrograms showed significant variations in two periods: between 5:15 a.m. and 9:10 a.m., coinciding with the start of daily activities, and between 6:25 p.m. and 8:50 p.m., associated with the return of the population to their homes. Figure 7 presents the spectrograms of the flow rate, velocity, and Reynolds number for the hydraulic system, showing the evolution of the oscillation frequency of these variables over time. Spectral analysis allows identifying fluctuations in flow, possible transients and cyclical patterns in water demand, which is essential for the detection of anomalies and the optimization of supply in water distribution networks.

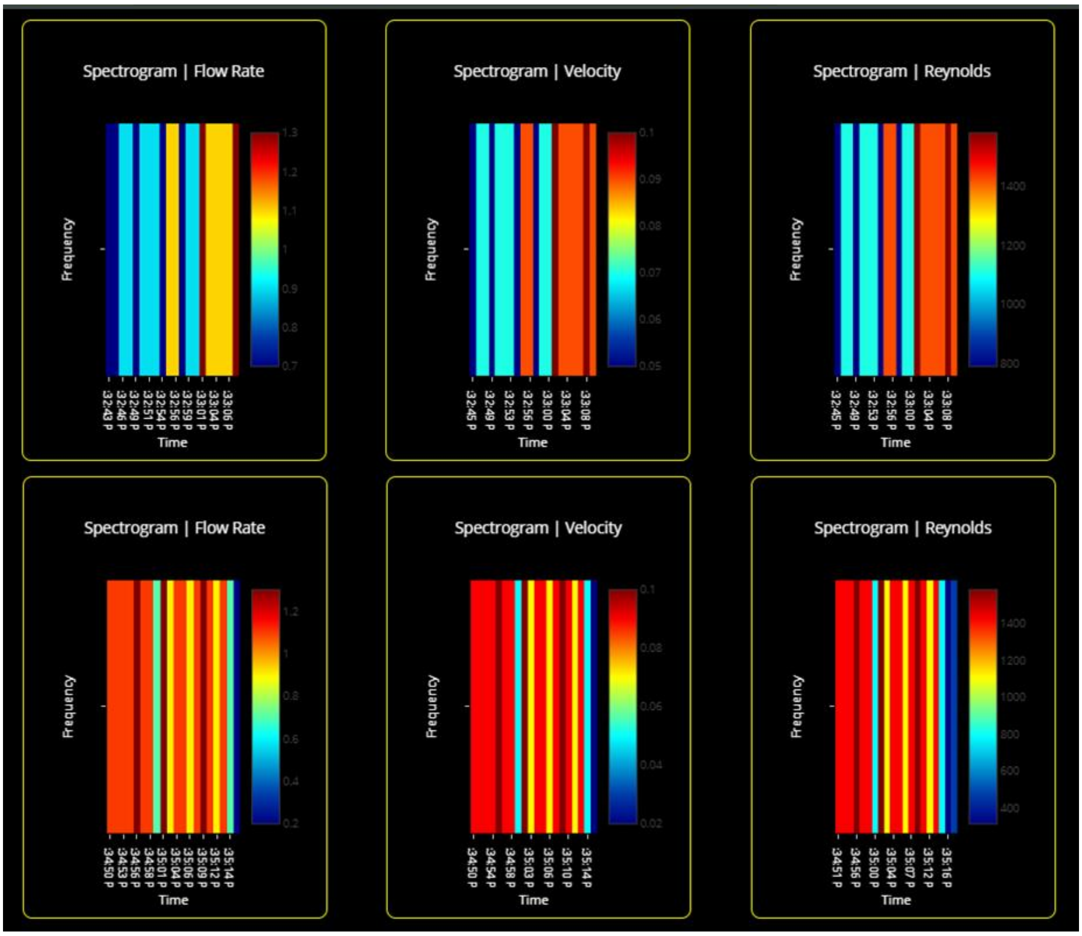

Figure 7. Spectrograms of flow rate, velocity, and Reynolds number show frequency variations over time

2.3. Real-time Signal Processing

This study uses HTML and JavaScript to fetch real-time flow data from ThingSpeak, using Channel ID and API Key. A fetch request to the API every second retrieves water flow measurements (L/min). The data is filtered with digital low-pass, high-pass and moving average filters to optimize signal stability. Low-pass filter attenuates vapor flow in closed systems, affecting measurements according to relative humidity [15]. Consequently, the low-pass filter is implemented with the recursive equation:

$$[i] = \alpha x[i] + (1 - \alpha) y[i - 1] \tag{1}$$

where $y[i]$ is the filtered signal, $x[i]$ is the value of the time series sensor signal, y α is the smoothing coefficient. This filter reduces high-frequency noise and stabilizes measurements, yet eliminates low frequencies, improving signals in digital processing and communications Shahid et al. (2015) [16], the following expression defines this type of filter:

$$y[i] = \alpha(y[i - 1] + x[i] - x[i - 1]) \tag{2}$$

Figure 8 shows the filters applied in real-time to the flow signal, optimizing data quality and reducing noise in the measurements.

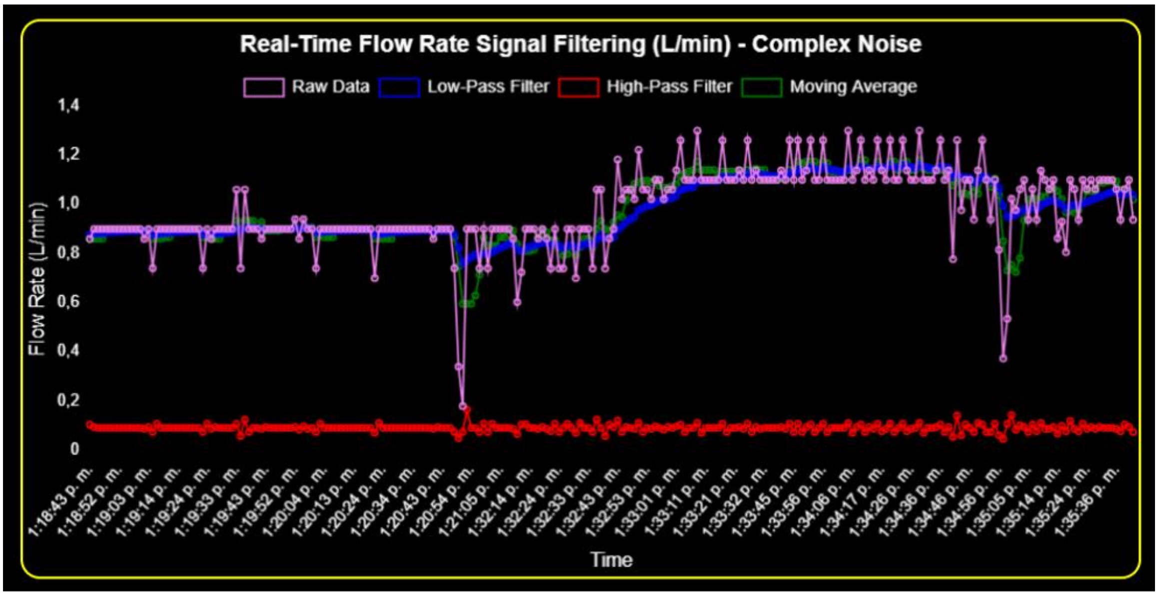

Figure 8. Real-time flow signal filtering. Raw and filtered flow rate data using low-pass, high-pass, and moving average filters to improve signal accuracy

The *WatAI* system is designed to adjust in real-time to second-to-second variations in flow rate, ensuring stability and accuracy in flow prediction. To handle sudden fluctuations and outliers, the system employs a real-time signal filtering process, using low-pass, high-pass, and moving average filters, reducing the impact of noise and eliminating spurious anomalies. Furthermore, the DNN model is continuously trained with historical data, allowing it to dynamically adapt to consumption trends and minimize prediction errors in the presence of sudden changes in flow.

The approach adopted by *WatAI* also includes anomalous event detection, comparing real-time readings with previously learned patterns. When the system detects an unexpected variation, it assesses its persistence and relevance through statistical analysis before classifying it as a critical event. This mechanism not only prevents the generation of false alarms but also optimizes the system's sensitivity to significant anomalies in the distribution network.

2.4. Dynamic Neural Network Implementation

For the development of the DNN, the last 1000 filtered flow data recorded by the sensor were used. This data is stored on the server and processed to define the neural network input. Thus, the code implements an DNN model in TensorFlow.js for real-time flow prediction, obtaining the data by querying through the ThingSpeak API (Application Programming Interface). Fetch requests are configured to retrieve water flow records and process them in a sequential model once filtered. The model features a 50-neuron hidden layer with ReLU activation, which is trained on a subset of historical data, optimizing with the Adam algorithm and minimizing error using MSE loss function. The network then generates predictions that are compared to actual values, assessing accuracy through MSE, MAE (Mean Absolute Error) and accuracy. For instance, it uses the Adam algorithm to optimize DNN (Deep Neural Network) training for real-time water quality monitoring [17].

Figure 9 represents the processing flow of the DNN for real-time flow prediction. The scheme is divided into three main modules: real-time data preparation, neural network processing and result evaluation. In the first stage, the first 1000 input data and labels are processed and passed through a dense layer of 50 units with ReLU activation, which allows modelling complex patterns in the time series. Thus, ReLU improves the classification of water images in IoT pollution monitoring systems [18]. ReLU also optimizes the performance of Machine Learning models to detect leaks [19]. Subsequently, the output of the neural network is compared with the actual values to calculate error metrics such as MSE and total loss, providing an adjusted real-time flow prediction. Finally, the results are presented in a dynamic interactive graph (Figure 10), where both the actual data and the DNN-generated predictions are visualized.

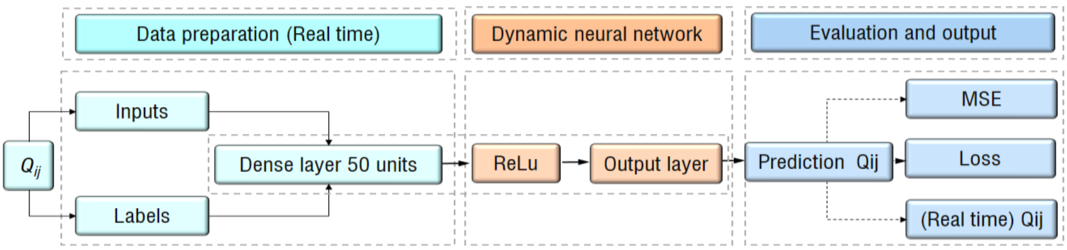

Figure 9. Dynamic neural network framework: Real-time data is processed through a dense layer with ReLU activation

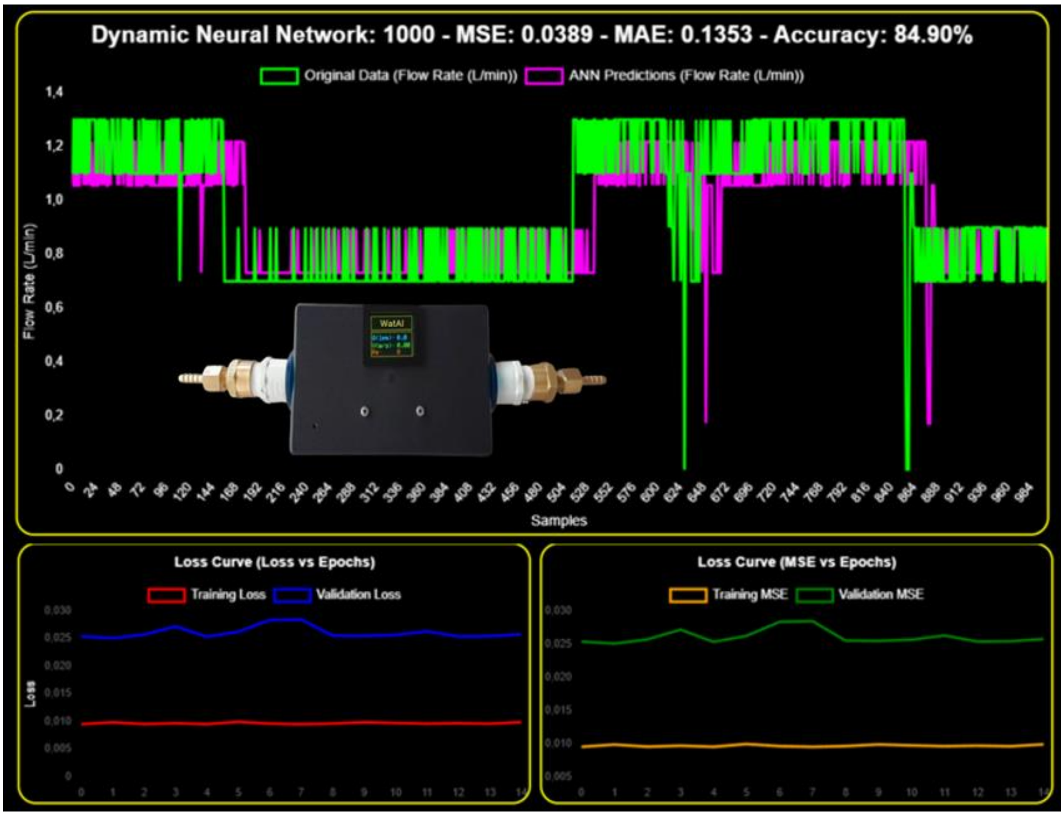

Figure 10. Neural network flow prediction (Real-time)

3. Results and Discussion

To validate the results obtained by the DNN programmed in HTML, a code was developed in Python (Colab) using TensorFlow to build and train an DNN to predict the flow in real-time. The data is obtained from a continuously updated Google Drive file and processed with Pandas and NumPy. To improve the efficiency of the model, the data is normalized with MinMaxScaler, scaling it to the range [0,1]. The neural network is configured with a dense hidden layer of 50 neurons and ReLU activation function, replicating the architecture proposed in the HTML code, followed by an output layer. The model is trained with the Adam optimizer and the MSE loss function, evaluating its performance on a set of 1980 test data using metrics such as MSE and MAE.

The results presented in Table 1 indicate that the optimal number of units in the dense layer was 50, so the model adopted this value. It was observed that, as the number of units increased, the values of the control statistics, such as MSE and MAE, did not show significant improvements. This suggests that increasing the complexity of the model does not necessarily lead to better performance and could lead to over-fitting without additional benefits in prediction accuracy.

Table 1. DNN performance for different dense layer units. Comparison of MSE, MAE, and Accuracy

Units in dense layer	MSE	MAE	Accuracy
10	0.000117	0.007188	0.002414
20	0.000113	0.008186	0.002530
30	0.000109	0.008099	0.003214
40	0.000114	0.009308	0.004412
50	0.000110	0.006510	0.003812

Figure 11 presents a comparison between the actual values and the flow predictions obtained using an DNN. The actual values (green) are plotted alongside the DNN predictions (dashed magenta line) to assess the accuracy of the model in predicting real-time flow variations. The fluctuations reflect the dynamic nature of water consumption at different times, where DNN attempts to capture and reproduce the demand patterns observed in the measured data.

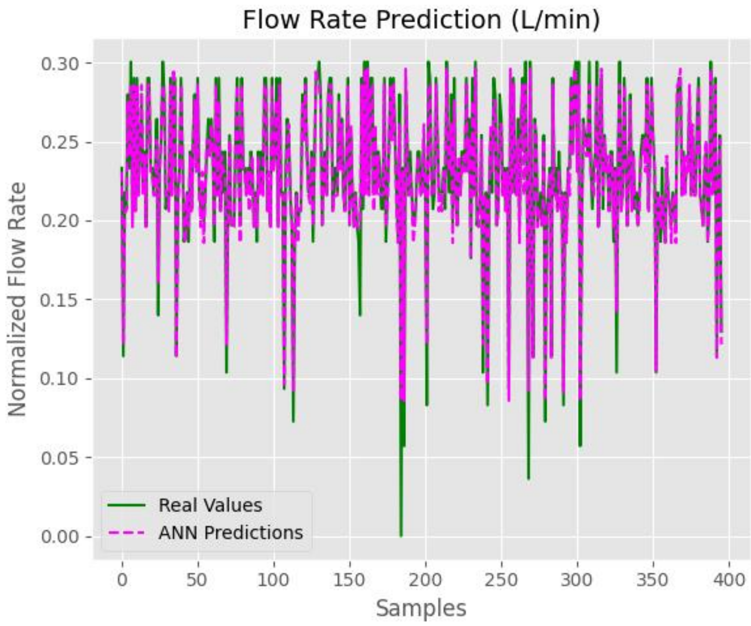

Figure 11. DNN flow rate prediction. Real vs. predicted flow rate, showing DNN performance in capturing

Table 2 presents the comparison of different activation functions in order to identify the one that optimizes the performance of the model in terms of error. The values of MSE and MAE are evaluated to determine which function gives the best accuracy in flow prediction.

Table 2. DNN performance for different dense layer units. Comparison of MSE, MAE, and Accuracy

Activation Function	Units in dense layer	MSE	MAE
ReLu	50	0.000162	0.006664
Sigmoid	50	0.000794	0.021809
Tanh	50	0.000398	0.014074
Leaky ReLu	50	0.000178	0.007575

The loss and MAE curves presented in Figure 12 show the performance of the DNN model over 200 epochs in real-time flow prediction. In the left plot, the training loss (blue) shows a progressive decrease and stabilizing at a value close to 0.001, while the validation loss (orange) remains low and stable, indicating that the model generalizes well with no evidence of overfitting affecting the unknown data in the learning process. On the other hand, in the right-hand plot, the training MAE (red) gradually decreases, while the validation MAE (purple) exhibits more fluctuation, reflecting the inherent variability of the flow data.

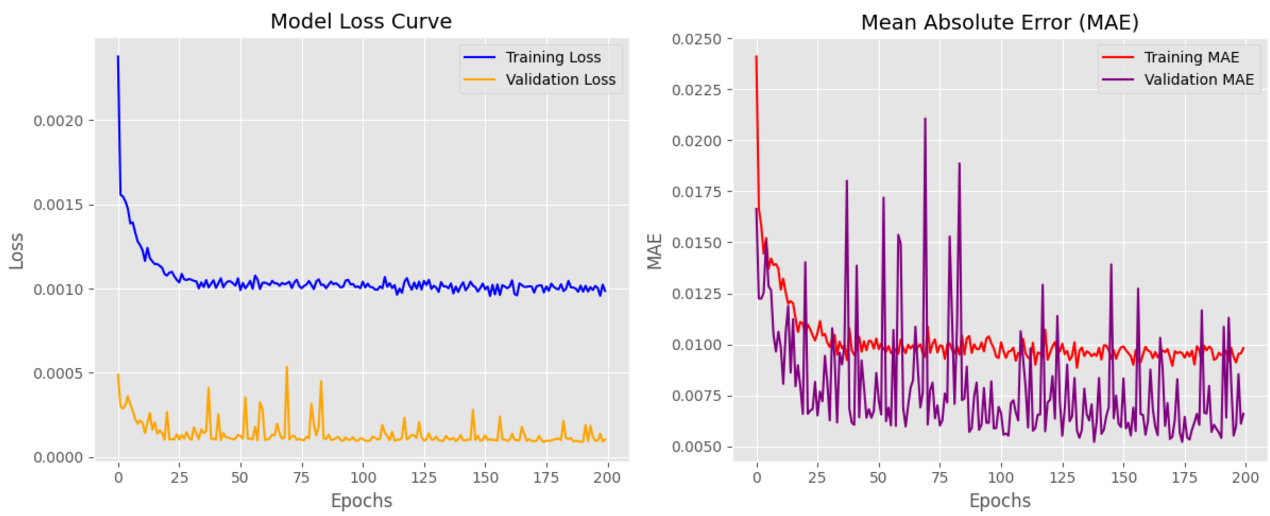

Figure 12. Training and validation metrics. Loss and MAE curves over 200 epochs, showing training and validation performance of the DNN model

Based on the above, it was determined that the optimal configuration of the DNN model in HTML is sequential, with a hidden layer of 50 neurons and ReLU activation. This approach balances accuracy and generalization in real-time flow prediction. Moreover, its web-based implementation optimizes computational capacity and guarantees immediate response.

MSE of 0.006510 reported for the DNN model is dynamic and evolves as the dataset expands over time. The study reveals that as the flow series increase in data volume, the MSE tends to decrease, leading to improved prediction accuracy. Unlike traditional models such as linear regression, which assume a fixed relationship between variables, the DNN model dynamically adjusts to variations in flow patterns, enabling it to capture complex nonlinear dependencies more effectively. This adaptability allows the model to refine its predictions as more historical data become available, enhancing its precision in real-time applications.

To ensure a comprehensive evaluation of model performance, additional metrics such as MAE and R-squared were considered. The MAE quantifies the average deviation between predictions and actual values, providing insight into the model's precision, while R^2 measures the proportion of variance explained by the model, indicating its predictive reliability. The findings confirm that the DNN model consistently outperforms traditional forecasting methods, particularly in highly dynamic and nonlinear environments. This superior performance demonstrates the model's robustness in real-time water demand prediction and anomaly detection, making it an effective tool for intelligent water resource management.

The *WatAI* prototype demonstrates an adaptive real-time response to variations in flow rate (Figure 12), as illustrated in Figures 13 and 14. In the first 15 minutes of operation, the model exhibits an MSE of 0.0235 and an accuracy of 60.80%, as it begins adjusting to the data stream. The hidden layer with 50 neurons and ReLU activation processes incoming flow rate values, while the Adam optimization algorithm refines weight updates to minimize prediction errors. The observed initial fluctuations suggest that the model is still adapting to real-time flow behavior, where anomalies and abrupt changes in water distribution affect prediction stability. Despite this, the multi-layer filtering system (low-pass, high-pass, and moving average filters) effectively mitigates transient noise, reducing the impact of outliers.

As time progresses, the model continuously refines its predictions, leading to improved performance metrics. By the 25-minute mark (Figure 14), MSE decreases to 0.0206, and accuracy increases to 73.10%, demonstrating the self-adaptive nature of the DNN. This performance enhancement results from the model's ability to integrate more historical data, refining the learned patterns and distinguishing between normal variations and genuine anomalies. The observed improvements indicate that the real-time calibration mechanism embedded in *WatAI* optimally adjusts to demand fluctuations, effectively reducing errors in water flow prediction

One of the key advantages of this approach is the ability to eliminate outliers and noise through an intelligent filtering mechanism, which ensures that the system does not overfit irregularities caused by sudden flow disruptions. The gradual alignment between DNN predictions and actual flow rate values suggests that the network effectively learns from its environment. As the model accumulates more real-time data, prediction reliability increases, allowing for more precise anomaly detection and flow estimation. The impact of low-pass and moving average filters is particularly evident in the later stages, as spurious fluctuations are suppressed, allowing the network to generalize effectively.

The *WatAI* system represents a significant advancement in real-time flow prediction and anomaly detection in water distribution networks, offering a unique contrast to previous AI-based approaches to water resource management. Unlike the hybrid IoT system developed by Adeleke et al. [3], which uses ANN and SVM models to monitor water quality and predict impurity levels, *WatAI* focuses on real-time flow variations, enabling instantaneous detection of anomalies such as leaks and blockages. While Adeleke et al. [3] optimized remote sensing and automated water treatment management, *WatAI* prioritizes continuous flow analysis and predictive adjustments using its DNN with ReLU activation and Adam optimization. Furthermore, WatAI's integration with low-pass, high-pass, and moving average filters ensures data accuracy by minimizing noise and avoiding false detections a critical feature that was not emphasized in previous water quality monitoring models.

Similarly, Bhati et al. [4] applied machine learning models, including Naïve Bayes and Decision Trees, to monitor water contamination in rural communities, significantly improving contamination detection. In contrast, *WatAI* applies AI-based models to predict and regulate water demand, optimizing urban water distribution systems where fluctuations and sudden consumption changes require real-time responses. Additionally, previous studies, such as Islam et al. [6], employed ML-based IoT devices to detect leaks, achieving high accuracy (98.96%) in identifying water losses. *WatAI* builds upon this approach by integrating DNN-driven real-time monitoring, allowing not only for leak detection but also for predictive flow control and network optimization. While prior research has successfully leveraged AI and IoT for water quality monitoring, leakage detection, and flood prevention, *WatAI* contributes to the field by offering an adaptive, self-improving system that enhances flow prediction, anomaly detection, and decision-making in real-time.

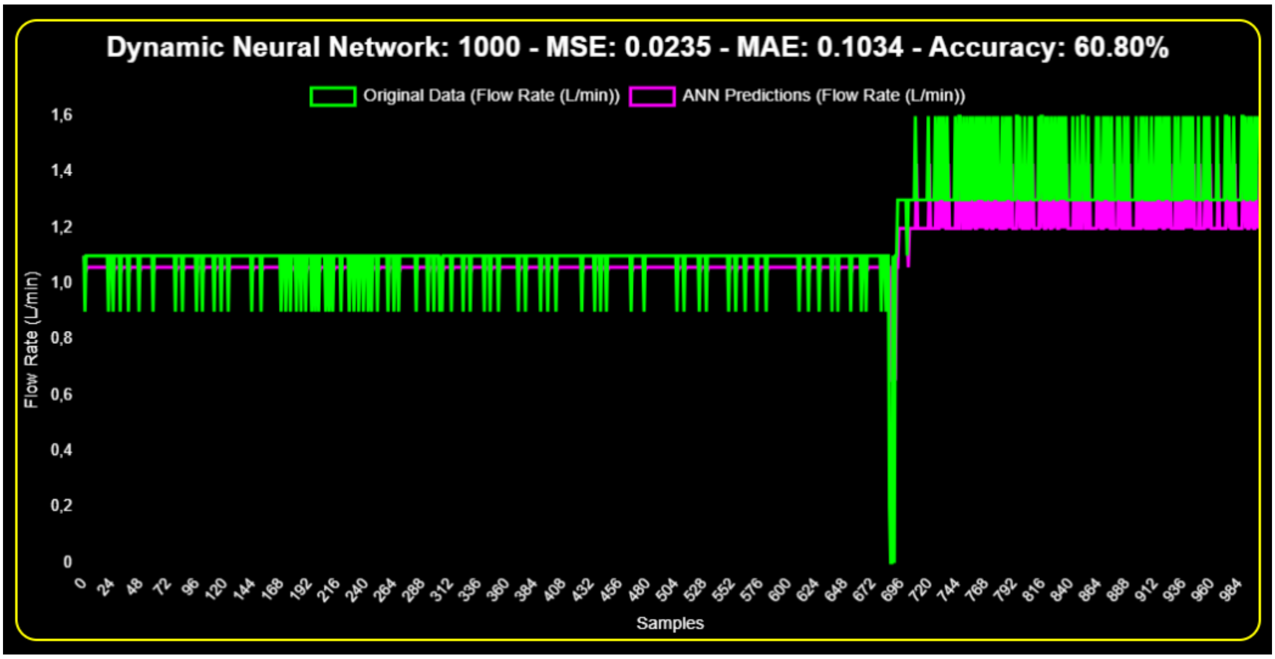

Figure 13. Flow disruption in the first 15 minutes of WatAI prototype operation

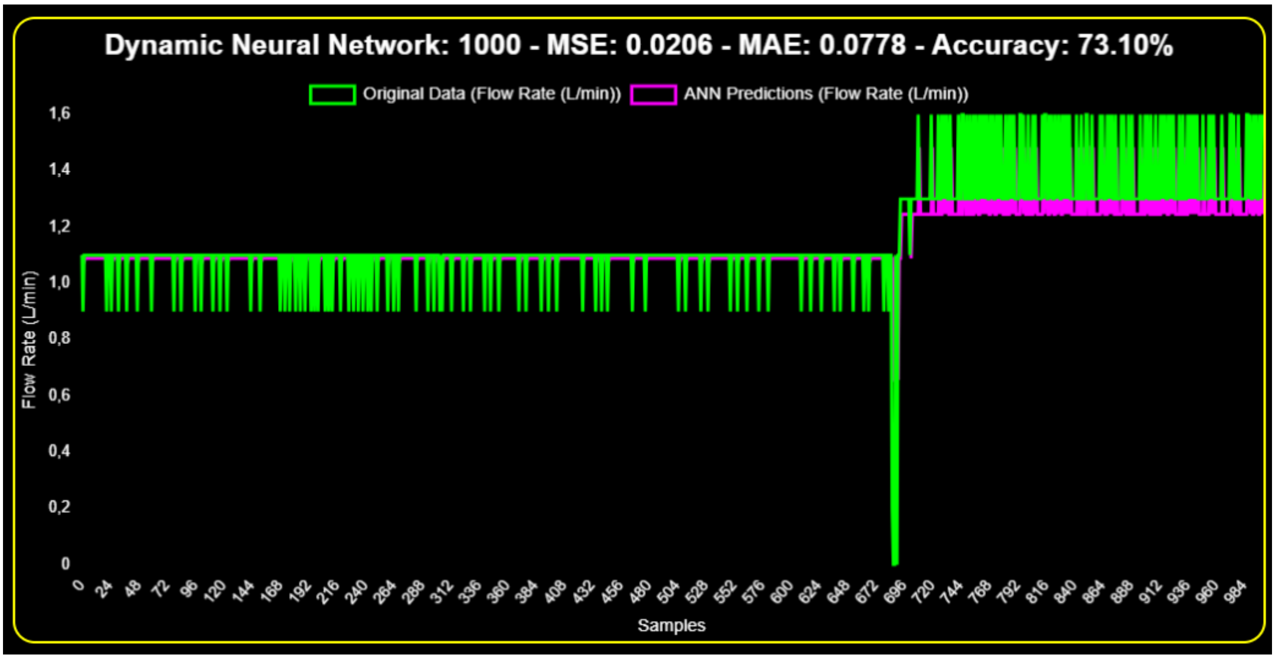

Figure 14. Flow disruption in the first 25 minutes of WatAI prototype operation

The results obtained with the *WatAI* prototype in real-time flow prediction using a DNN, implemented in an IoT environment, show a significant improvement in the accuracy of the model when using a hidden layer of 50 neurons with ReLU activation. Comparing these findings with previous studies, it is observed that similar approaches have used static deep learning models for the estimation of hydraulic variables; however, most of them do not operate in real-time. In contrast, the approach proposed in this study integrates hydraulics, IoT and early warning systems, demonstrating the feasibility of a DNN capable of predicting flow behavior with high temporal resolution (one second). The implementation on a web platform guarantees instantaneous response, optimizing data management and facilitating its integration into water distribution network monitoring infrastructures. For future research, it is recommended to explore more advanced architectures, such as LSTM or GRU (Gated Recurrent Unit) networks, which could improve the capture of temporal patterns and widen the prediction window, allowing a better estimation of water demand for strategic water resource planning.

4. Conclusions

The development and implementation of the *WatAI* prototype demonstrate the feasibility of a DNN capable of real-time flow monitoring in a water distribution network. Unlike traditional deep learning models, which operate statically, *WatAI* integrates ReLU activation and Adam optimization, enabling it to adapt to variations in flow rate every second. This real-time adjustment improves the accuracy of anomaly detection, allowing for the identification of leaks, blockages, and unexpected consumption patterns. Additionally, the system implements low-pass, high-pass, and moving average filters, ensuring that noise and signal distortions do not affect measurement reliability. One of the most significant advantages of *WatAI* is its ability to continuously update and refine predictions as more historical data become available.

The results show that MSE values improve over time, demonstrating that larger datasets contribute to greater predictive accuracy. This makes the system particularly effective in managing water demand, where fluctuations occur due to changing consumption patterns. Moreover, missing data caused by transmission failures. *WatAI* uses machine learning to distinguish anomalies from normal flow variations, thereby reducing false positives. IoT sensors, real-time modeling, and web visualization enhance its functionality, optimizing water management by improving efficiency and reducing losses and contributing to decision-making.

The integration of artificial intelligence, IoT, and early warning systems in the *WatAI* framework enables instantaneous response to variations in water distribution networks, facilitating the implementation of smart monitoring infrastructures. The system's open-access web platform allows real-time flow visualization, anomaly detection, and automated notifications, enhancing operational efficiency. By comparing real-time measurements with historical trend analysis and statistical thresholds, *WatAI* minimizes errors and ensures accurate demand forecasting. The use of adaptive learning strategies, combined with real-time filtering techniques, improves data accuracy and system performance.

A key finding is that the model's predictive capability improves as historical data accumulates, suggesting that continuous training enhances forecasting precision. Compared to traditional models such as linear regression, which assume static relationships, *WatAI* dynamically adjusts to flow variations, capturing nonlinear dependencies with high accuracy.

For future research, it is recommended to explore the incorporation of GRU (Gated Recurrent Units) and LSTM (Long Short-Term Memory) networks to further improve consumption trend detection and enhance predictive capabilities. Additionally, refining self-correcting algorithms for missing data and integrating more advanced anomaly classification techniques could strengthen the model’s resilience in complex urban water systems. The findings reinforce the potential of AI-based water management solutions to optimize distribution, reduce waste, and support sustainable urban planning in cities like Bogotá.

5. Declarations

5.1. Data Availability Statement

The data and code from this study are available for academic use, provided that proper citation is given to the author and the study. Access is provided through the following links:

- Ladino-Moreno, E. O. (2025). Code Python WatAI. https://doi.org/10.5281/zenodo.14795045.
- Ladino-Moreno, E. O. (2025). Code Arduino WatAI. https://doi.org/10.5281/zenodo.14795072.
- Ladino-Moreno, E. O. (2025). Data flow. https://doi.org/10.5281/zenodo.14795085.
- Ladino-Moreno, E. O. (2025). WatAI: Intelligent system for predicting. https://doi.org/10.5281/zenodo.14795967.

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5.4. Conflicts of Interest

The author declares no conflict of interest.

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