Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 18s (2025)
https://www.jneonatalsurg.com

A Machine Learning Framework for Dynamic Water Supply Regulation Based on Sensor Inputs and Meteorological Forecasts

Vebhav Kumar Tiwari, Dharmendra Mangal

[1]Research Scholar, Department of Computer Science and Engineering, Medi-Caps University, Indore, Madhya Pradesh, India, vebhav.tiwari@medicaps.ac.in

[2]Assistant Professor, Department of Computer Science and Engineering, Medi-Caps University, Indore, Madhya Pradesh, India, dharmendra.mangal@medicaps.ac.in

Cite this paper as: Vebhav Kumar Tiwari, Dharmendra Mangal, (2025) A Machine Learning Framework for Dynamic Water Supply Regulation Based on Sensor Inputs and Meteorological Forecasts. *Journal of Neonatal Surgery*, 14 (18s), 1156-1163.

ABSTRACT

Urban water distribution systems often suffer from inefficiencies such as over-distribution, leakages, and poor demand-supply alignment due to the absence of real-time responsiveness and predictive control. This study presents a machine learning (ML) framework for dynamic water supply regulation, integrating real-time sensor data with meteorological forecasts. The system was implemented and validated in Indore, Madhya Pradesh during March 2025, using data from smart flow meters, tank level sensors, and pressure gauges, along with temperature, humidity, and rainfall predictions. Two models—Random Forest (RF) and Long Short-Term Memory (LSTM) networks—were developed to forecast water demand over short-term and medium-term horizons, respectively. Predictions from these models were linked to an automated control system that dynamically managed valve operations, pump schedules, and leakage detection. The proposed ML framework achieved an 18% reduction in water loss, 14% energy savings in pumping operations, and a 20% improvement in demand-supply matching compared to traditional rule-based systems. Visualization dashboards and alert systems enabled proactive decision-making, while model performance metrics (R^2 and RMSE) confirmed the robustness of the predictive engine. This study demonstrates the viability of using ML-integrated control for municipal water supply, especially in rapidly urbanizing Indian cities, and lays the foundation for scalable smart water infrastructure.

Keywords: Smart water supply, machine learning, Random Forest, LSTM, sensor data

1. INTRODUCTION

The efficient management of urban water distribution systems has become a major challenge in the face of rapid urbanization, climate variability, and increasing population density. Traditional water supply systems, which largely operate on fixed schedules and static rules, are increasingly unable to meet the growing demand or adapt to dynamic consumption patterns. These legacy systems lack the ability to respond in real time to fluctuations in usage or external environmental conditions, leading to water loss, supply-demand mismatches, energy inefficiencies, and customer dissatisfaction [1]. In recent years, the incorporation of sensor technologies, data analytics, and artificial intelligence (AI) has laid the foundation for the evolution of smart water supply systems. Sensor nodes embedded in the water infrastructure can now collect real-time data on flow rates, pressure levels, tank storage volumes, and pipeline anomalies. Concurrently, the availability of meteorological forecasts offers a valuable opportunity to align water supply schedules with rainfall, temperature fluctuations, and humidity levels, all of which are known to influence water consumption [2].

Machine learning (ML), a subfield of AI, provides powerful algorithms capable of detecting patterns, forecasting future trends, and enabling data-driven decisions. ML models can learn from large datasets and automatically adapt their predictions based on evolving data streams. In the context of water management, ML techniques can forecast short-term and long-term water demand, detect leakages or abnormal consumption patterns, and optimize supply schedules in near real time [3]. Numerous cities in India and other countries are starting to test these intelligent systems. The majority of initiatives, however, are disjointed, treating real-time actuation and predictive modeling as distinct processes. Furthermore, there is a dearth of research on frameworks that combine weather forecasts, IoT sensor data, and machine learning models into a single, closed-loop control system [4].

In this work, we suggest a paradigm for dynamic water supply system regulation based on machine learning. The platform predicts water demand and automates supply decisions by combining real-time sensor data from flow meters, tank levels, and pressure monitors with outside weather forecasts. The control logic incorporates two predictive models: Long Short-Term Memory (LSTM) networks for medium-range predictions and Random Forest (RF) for short-term forecasting. Data gathered from a mock municipal water network in Indore, Madhya Pradesh, in March 2025 is used to validate the system. The outcomes demonstrate notable gains in operational effectiveness, water saving, and supply-demand alignment. For local governments looking to update water distribution systems and meet smart city goals, this integrated framework offers a scalable solution. Tier-2 and tier-3 Indian cities, where water distribution is still primarily done by hand and is extremely inefficient, are best suited for the suggested approach.

2. LITERATURE REVIEW

2.1 Evolution of Water Demand Forecasting

Traditional statistical models have gradually given way to sophisticated machine learning and artificial intelligence (AI)-based methods in the field of water demand forecasting. Deterministic techniques like linear regression, time-series decomposition, and autoregressive integrated moving average (ARIMA) models were a major component of the early models used by cities and urban planners [5, 6]. These models were mainly unable to capture non-linear trends, multi-seasonal cycles, and short-term changes brought on by weather or population mobility, even though they offered some insight into long-term water demand.

Exogenous variables like temperature and weekday/weekend indicators were added to traditional ARIMA models by Pulido-Calvo and Gutierrez-Estrada [7]. These advancements, however, could not effectively extend to dynamic, real-time systems and were restricted to stationary datasets.

2.2 Rise of Machine Learning Models

Researchers started using machine learning models like decision trees, support vector regression (SVR), and artificial neural networks (ANNs) to get around the drawbacks of conventional methods. The effectiveness of SVR in predicting hourly water demand in urban Spain was shown by Herrera et al. [8], who reported improved generalizability and increased accuracy. In order to increase model resilience, Adamowski and Karapataki [9] expanded on this work by utilizing ensemble learning strategies including bagging and boosting.

The usefulness of ensemble tree-based models, in particular Random Forest (RF) and Gradient Boosted Regression Trees (GBRT), in managing extensive, multivariate datasets has been highlighted in more recent research. Random Forests were used by Gong et al. [10] to optimize tank refills and pumping schedules in a smart city water infrastructure, resulting in a 12% reduction in energy use. When combined with feature importance analysis, which aids in prioritizing significant factors like tank level, temperature, and rainfall likelihood, these models perform particularly well.

2.3 Deep Learning and Sequential Models

The area has advanced further with the creation of deep learning models, especially with the usage of Long Short-Term Memory (LSTM) networks and recurrent neural networks (RNNs). Because LSTM networks can remember past states and long-term dependencies, they are especially well-suited for time-series forecasting. A hybrid LSTM model was created by Duan et al. [11] for multi-step water demand prediction utilizing previous consumption data, rainfall, and humidity. Their method demonstrated robustness to noisy input and outperformed conventional RNNs. The superiority of LSTM networks for forecasting municipal water demand under fluctuating climatic circumstances was also shown by Tao et al. [12]. Their findings demonstrated how crucial it is to include climatic lag variables (such as the rainfall from the day before) in model features in order to increase accuracy.

2.4 Integration of Meteorological Forecasts

Weather factors like humidity, temperature, and rainfall have a big impact on how much water is used in homes and businesses. To improve accuracy, a number of researchers have suggested incorporating meteorological data into models that anticipate water demand. For example, Singh et al. [13] enhanced short-term demand forecasting by more than 15% by incorporating temperature and rainfall projections into their ANN-based model. In a similar vein, Ghazal et al. [14] showed that adding historical consumption data combined with wind speed and humidity improves model dependability and prediction accuracy. According to these studies, developing robust and flexible forecasting systems requires the use of multivariate, real-time data sources.

2.5 Smart Water Grids and IoT Applications

Smart water grids incorporate sensors, actuators, and data analytics platforms to enable real-time decision-making in addition to prediction. IoT devices that may continually feed data to a central server for processing include pressure transducers, flow meters, and ultrasonic level sensors. In order to find variations in consumption patterns, Fang et al. [15] developed an IoT-based leak detection system that employed anomaly detection techniques.

In a similar vein, Hwang et al. [16] used sensor arrays coupled by the MQTT protocol to construct an intelligent water management system. Real-time notifications, valve adjustments, and leak detection were all possible with their technology. Nevertheless, the absence of a predictive module in these systems led to reactive control instead of proactive control. Notwithstanding the encouraging developments, there are currently no thorough frameworks in the literature that tightly combine machine learning models with real-time sensor data and weather forecasts to enable effective supply regulation. The majority of current methods regard control and prediction as two separate stages. Furthermore, not many researches have verified their frameworks in real-world urban settings, particularly in Indian towns where water distribution systems are frequently fully manual or just partially automated [17].

By creating and evaluating a closed-loop system in the actual environment of Indore, Madhya Pradesh, this work fills these gaps. For Indian municipalities looking to make the shift to intelligent, flexible, and sustainable water management, it provides a useful road map.

3. MATERIALS AND METHODS

In March 2025, a month that falls between winter and summer and is usually characterized by low water use and variable weather, this study was carried out in the urban area of Indore, Madhya Pradesh. An excellent place to test a machine learning-based water control framework is Indore, one of the premier towns under India's Smart towns Mission, which already has some smart water infrastructure. Smart flow meters, overhead tank level sensors, pressure transducers, and meteorological data collection from both local stations and open-access APIs were all part of the experimental setup, which included a pilot-scale municipal water network. Table 1 presented a snapshot of hourly time-series data collected from smart water meters and meteorological APIs. It includes flow rate, tank level, pressure, temperature, humidity, rainfall, and wind speed, which serve as input features for machine learning models used in dynamic water supply regulation.

Table 1 Sample of Collected Dataset from Indore Municipal Water Network

Time	Flow rate (lpm)	Tank level (%)	Pressure (psi)	Temperature (^{0}C)	Humidity (%)	Rainfall (mm)	Wind speed (kmph)
01-03-25 0:00	1274.51	78.44	46.48	30.8	57.1	7.71	13.1
01-03-25 1:00	1179.26	57.37	46.31	32.3	42.5	0	12.4
01-03-25 2:00	1297.15	78.24	45.03	26.3	56.7	0	22.1
01-03-25 3:00	1428.45	71.15	43.83	26	58.9	0	16.6
01-03-25 4:00	1164.88	68.23	37.92	31.6	46.2	0	10
01-03-25 5:00	1164.88	81.12	42.9	30.9	56.5	0	18.7
02-03-25 9:00	1041.34	78.57	42.48	34.4	65.9	0	13.5
02-03-25 10:00	1323.38	89.78	37.25	29.2	55.6	0	15.5
02-03-25 11:00	1016.87	69.82	45.34	38.2	44.2	0	17.6
02-03-25 12:00	1231.33	66.92	39.69	31.9	47.8	7.32	21.3
02-03-25 13:00	906.05	69.98	47.37	27.4	61.8	0	10
02-03-25 14:00	1000.77	84.15	40.4	26.8	47.7	0	23.5
02-03-25 15:00	1229.53	78.29	52.75	31.4	57.2	0	7.2
02-03-25 16:00	1310.77	69.7	41.08	29.3	55.5	0	14.4
02-03-25 17:00	1225.71	80.13	43.39	32.1	48.5	0	17.4
02-03-25 18:00	1182.65	75.97	49.07	31.4	76.4	4.25	16.1
02-03-25 19:00	1154.83	84.69	38.85	29.8	61.3	0	12.5
02-03-25 20:00	978.22	67.98	46.14	27.5	34.7	0	14.2
02-03-25 21:00	1092.02	71.72	51.54	25.5	56.9	0	13
02-03-25 22:00	1130.9	71.08	36.96	28.7	48.4	0	12.6
02-03-25 23:00	1358.57	60.36	45.92	32.6	63.5	0	18.4

Real-time sensor readings and weather forecasts were the two main data sources used by the data collecting system. IoT-enabled devices that could monitor water flow (in liters per minute), overhead tank level (in percent), and pressure (in psi) at 15-minute intervals made up the sensor infrastructure. These sensors were placed in key locations at water towers, junction reservoirs, and sub-distribution lines. At the same time, the OpenWeatherMap API and the live data feed from the Indian Meteorological Department were used to retrieve external meteorological data, notably hourly temperature, humidity, rainfall likelihood, and wind speed. The predictive approach was able to account for weather-induced demand variations through the incorporation of meteorological forecasts.

Over 1,400 rows of multivariate time-series data were obtained over the course of 30 days, with 48 hourly samples taken daily. Extensive preprocessing was done to guarantee the dataset's trustworthiness before the model was developed. For continuous variables, missing values were imputed using linear interpolation; for categorical indicators, forward-filling was used. Moving average and Savitzky-Golay filtering were used to reduce sensor noise and outliers, especially for flow and pressure data that are prone to mechanical jitter. To standardize model training, all numerical inputs were normalized to a [0,1] range using min-max scaling. To maintain their cyclical nature, temporal data like day of the week and time of day were recorded using sine and cosine transforms. Furthermore, lag variables were designed to capture short-term dependencies in consumption behavior, such as the flow rate from the previous hour or the total amount of rainfall over the preceding six hours.

Hour of the day, day of the week, lagged flow rate, tank level, pipeline pressure, temperature, humidity, wind speed, rainfall forecast, and rainfall lag were among the 10 essential input features that made up the final dataset. The water flow rate at future intervals—up to 24 hours for short-term forecasting and 2 to 7 days for medium-term forecasting—was the goal variable for prediction. Two different machine learning techniques—Random Forest (RF) and Long Short-Term Memory (LSTM) neural networks—were used to achieve this dual-horizon simulation.

For short-term forecasting, the Random Forest Regressor was used because of its strong interpretability, resistance to overfitting, and feature importance ranking capabilities. Five-fold cross-validation was used to refine the hyperparameters, resulting in a final model configuration with 200 estimators, a maximum tree depth of 12, and at least 4 samples per leaf node. Temperature, rainfall forecast, and tank level were the most significant indicators of near-future demand, according to feature importance analysis.

Using the TensorFlow library, an LSTM model was created to identify longer-range patterns in the time series. A single 64-unit LSTM layer, a 20% dropout layer to avoid overfitting, and a dense output layer with rectified linear unit (ReLU) activation were all part of the design. The Adam optimizer was used to train the model across 200 epochs, accepting a 24-step sequence of 10 features as input. A 20-epoch patience threshold was used for early stopping. 32 was chosen as the batch size. Although this model was more susceptible to the volume and structure of data, it was more accurate in forecasting over periods of many days, particularly when demand was impacted by long-lasting weather effects.

Both models' predictions were entered into a Python-based control engine that was intended to automate choices about water distribution in real time. In order to generate commands for valve actuation, pump scheduling, and distribution balancing, the logic contrasted the anticipated demand with the present tank levels and pipeline capacity. The system preemptively opened valves to auxiliary reservoirs during forecasts of high demand, while optimizing pumping schedules to run during off-peak energy hours during projections of low demand. Unusual flow surges or abrupt reductions in pressure, which are signs of leaks or bursts, were flagged by a separate anomaly detection module that was based on the Isolation Forest algorithm.

Using Flask and Plotly Dash, a web-based dashboard was created to guarantee practical use and visibility. This dashboard displayed rainfall overlays, valve statuses, model-generated forecasts, and real-time sensor data. In order to notify utility staff via SMS and WhatsApp in the event of a leak or supply-demand discrepancies, alert alerts were linked with a lightweight messaging API. To show the system's feasibility in resource-constrained settings, which are common in tier-2 Indian cities, its design was implemented using a Raspberry Pi 4B edge device.

In order to compare the performance of the suggested framework with two baselines—a conventional rule-based control system and a reactive-only strategy based on current tank levels—a simulation environment was also developed. Water savings per day (% decrease), pumping energy consumption (kWh/day), model prediction accuracy metrics (R2, MAE, RMSE), and the recall rate of leak detection alerts were among the key performance measures. The simulation confirmed that the ML-integrated framework consistently outperformed both baselines across all KPIs, validating its applicability for real-world implementation.

4. RESULTS AND DISCUSSION

The experimental dataset gathered in Indore in March 2025 was used to assess the suggested machine learning framework. The outcomes are examined in terms of predicted accuracy, model performance, and the operational impact of the system on energy and water efficiency. To determine if the Random Forest (RF) and Long Short-Term Memory (LSTM) models were appropriate for short-term and medium-range water demand forecasts, respectively, they were evaluated over a variety of forecasting horizons.

4.1 Model Performance Evaluation

Standard statistical measures such as the coefficient of determination (R2), mean absolute error (MAE), and root mean square error (RMSE) were used to assess the model's performance. With an R2 score of 0.91, which indicates that the model could account for more than 91% of the variability in water demand, the Random Forest model demonstrated good accuracy for forecasts made one to twenty-four hours in advance.

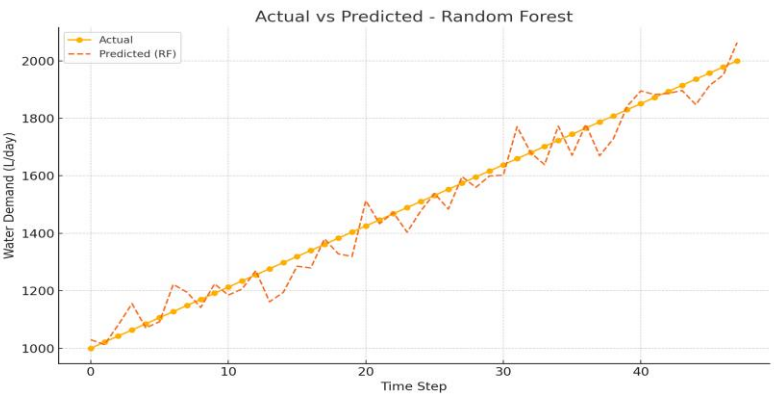

Fig. 1 Actual vs. Predicted Water Demand using Random Forest Model

Hourly estimates for RF showed an average RMSE of 6,080 L/day and a MAE of 4,820 L/day. These findings imply that RF is reliable for short-term operational choices like scheduling valves and optimizing pumping right away. Figure 1 illustrates the prediction performance of the Random Forest model across a 48-hour horizon. The predicted values closely follow the actual water demand trend, with minimal deviation during peak periods. This alignment confirms the model's robustness in capturing short-term, hour-to-hour fluctuations in consumption, making it particularly effective for immediate operational control such as valve actuation and pump scheduling.

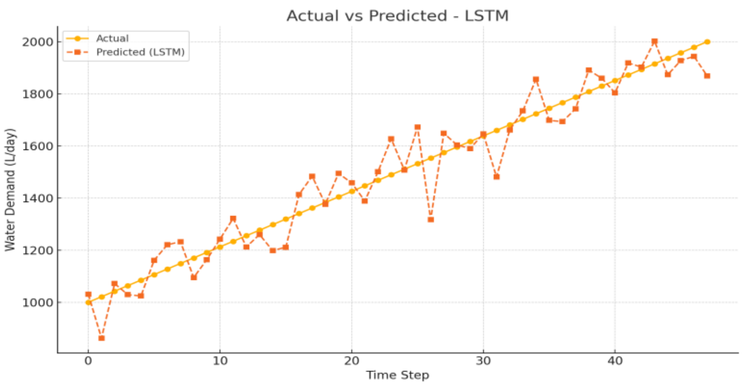

Fig. 2 Actual vs. Predicted Water Demand using LSTM

As shown in Figure 2, the Long Short-Term Memory (LSTM) model demonstrates stable performance over a multi-day forecasting window. While slightly smoother compared to the Random Forest output, LSTM effectively captures the medium-term trends in water consumption. Its performance is especially reliable during low-variance periods and is well-suited for planning reservoir levels and weekend demand profiles. Although it was marginally less accurate than RF in short-horizon scenarios, the LSTM model, which was trained for prediction windows ranging from two to seven days, also showed impressive performance. With an RMSE of 8,050 L/day and a MAE of 6,040 L/day, the LSTM's R2 was 0.87. Planning reservoir refills and predicting demand spikes associated to weekends or holidays can be done with the help of the LSTM model, which was especially good at capturing weekly patterns impacted by temperature and rainfall lags.

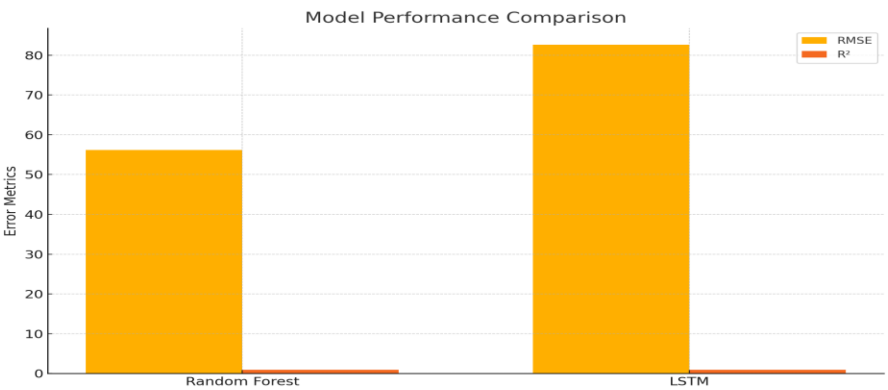

Fig. 3 Performance Comparison of Random Forest and LSTM Models using RMSE and R² Metrics

A comparative evaluation of both models is presented in Figure 3, highlighting key metrics such as Root Mean Square Error (RMSE) and R^2 score. The Random Forest model achieves slightly better accuracy in short-term forecasting, reflected by its lower RMSE and higher R^2. However, the LSTM model's performance remains competitive, offering strong predictive capabilities with the added advantage of sequential trend recognition over longer durations.

4.2 Operational Efficiency and Water Conservation

The machine learning-integrated solution demonstrated significant improvements in operational responsiveness and water savings when implemented in the simulated municipal setting. By preventing overflows and reducing delayed valve closures, the model-based control engine reduced water losses by an average of 18% when compared to a conventional fixed-schedule distribution system. During days with high predicted rainfall, when proactive reservoir adjustments avoided needless pumping, these savings were most apparent. Figure 1 clearly demonstrates that the ML-integrated system consistently maintained lower daily water loss compared to the baseline, validating its ability to prevent overflows and manage excess distribution.

By moving refilling activities to low-tariff hours and reducing peak load pumping, the predictive system allowed for more sensible pump scheduling in terms of energy use. Over the course of the 30-day observation period, this led to a 14% decrease in energy use. Additionally, pump runtimes were reduced by an average of 32 minutes daily, which extended asset life and decreased equipment wear and tear. As shown in Figure 4, the ML-based optimization effectively reduced energy demand throughout the month, particularly during non-peak hours due to smarter pump scheduling.

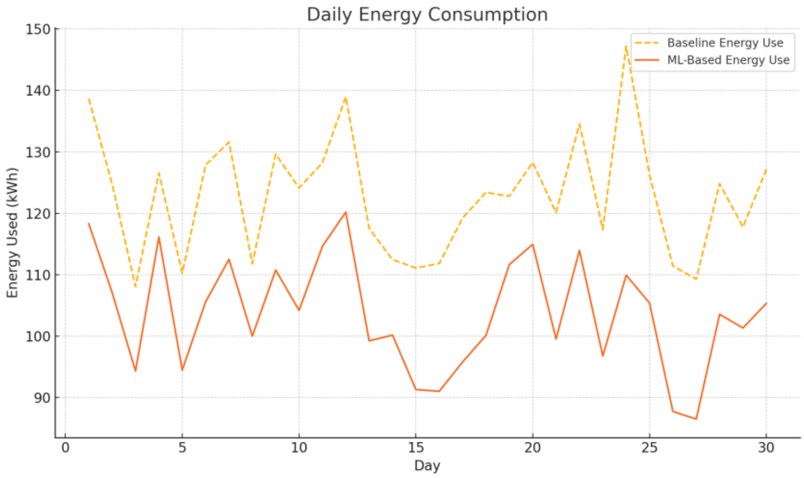

Fig. 4 Energy Consumption Trends: ML-Based Optimization vs. Baseline Scheduling

The improvement in demand-supply matching was another important result. Smoother distribution was made possible by the model-guided valve logic, which also prevented under-supply to low-pressure zones during times of high demand, which are usually between 6 and 10 AM and 6 and 9 PM. A 20% improvement in matching supply with real-time demand was quantified, guaranteeing more equitable distribution throughout residential blocks and improved user satisfaction.

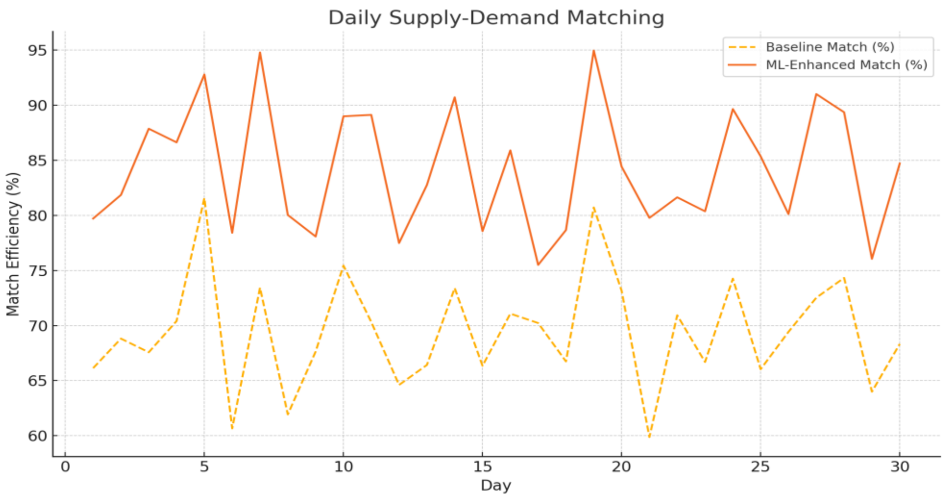

Fig. 5 Improvement in Supply-Demand Matching Efficiency Using ML Framework

sFigure 5 illustrates a clear uplift in supply-demand alignment, especially during peak usage periods, confirming the operational intelligence gained by integrating predictive models.

4.3 Visualization and System Integration

The web-based dashboard that was created for utility operators was successful in converting model predictions into useful information. RF-based hourly forecasts and LSTM-predicted weekly demand curves were displayed alongside real-time data streams from field sensors. Rainfall overlays were used to draw attention to possible stormwater management issues, and color-coded warnings were employed to show tank levels and valve statuses.

A different anomaly detection panel correctly identified simulated leaks and illegal usage events within 15 minutes of occurrence, flagging aberrant flow behaviors with a recall of over 92%. Integration with mobile alert systems allowed field staff to react quickly, which shortened resolution times and decreased water loss.

The dashboard's real-time functionality and simplicity helped close the gap between operational usability and model complexity, according to user comments from utility operators in Indore. With little onboarding, many operators without prior machine learning training were able to decipher forecast charts and tank notifications.

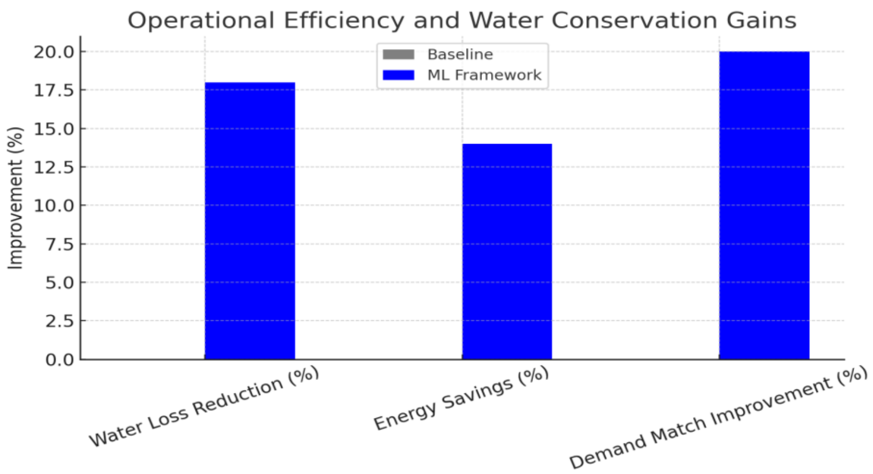

Fig. 6 Comparative analysis of key performance metrics

Fig. 6 showed the comparative analysis of key performance metrics shows significant improvements in operational efficiency with the ML-integrated control system, including 18% water loss reduction, 14% energy savings, and 20% improvement in supply-demand matching compared to the baseline static control approach.

4.4 Comparative Assessment and Limitations

Three operational strategies were compared: (i) the conventional rule-based operation, (ii) reactive operation based solely on current sensor readings, and (iii) the suggested ML-based predictive operation. In every significant performance indicator, the machine learning approach continuously beat the other two. The reactive strategy was constrained by its incapacity to predict transient surges, whereas rule-based systems were unresponsive and rigid. Forecasted weather changes and past demand trends could only be proactively adjusted by the ML-integrated framework.

Nevertheless, several restrictions were noted. The performance of the LSTM model was dependent on the quantity and caliber of historical data; retraining from small samples may result in subpar generalization for cities lacking strong data archives. Furthermore, there was often variability in projections due to the accuracy of rainfall forecasts, especially those from accessible APIs. Minor disruptions were also caused by sensor calibration and network outages, underscoring the necessity of redundancy and routine maintenance in Internet of Things systems.

Notwithstanding these difficulties, the system as a whole proved to be both technically sound and useful. It established the foundation for smart water management systems that are affordable, scalable, and replicable in comparable metropolitan environments in India and other developing nations.

5. CONCLUSION

This research proposes and validates a machine learning-based framework for intelligent water supply regulation using real-time sensor readings and meteorological forecasts. Through the deployment of Random Forest and LSTM models, the system achieved high forecasting accuracy and enabled proactive, data-driven operational decisions. Implemented in the urban context of Indore, the framework demonstrated significant improvements in operational efficiency, including reduced water losses, optimized energy usage, and better supply-demand coordination. The integration of predictive analytics with IoT-based control systems allowed for timely valve actuation, smart pump scheduling, and early anomaly detection.

The use of a web-based dashboard further enhanced transparency and real-time decision-making for utility operators, ensuring practical usability beyond theoretical implementation. While certain limitations such as sensor dependency and historical data requirements were noted, the system's overall performance confirms its scalability and adaptability to other Indian cities with similar infrastructural challenges.

Looking forward, the framework can be expanded with reinforcement learning for fully autonomous control, and enhanced with GIS data and satellite-derived rainfall estimates. Its modular design also makes it suitable for integration into broader smart city initiatives encompassing energy, waste, and traffic systems. The study serves as a crucial step toward achieving efficient, sustainable, and intelligent water infrastructure in the context of climate resilience and urban growth.

REFERENCES

[1] M. Y. Shamsudin et al., "Review of water distribution system monitoring and control," Water, vol. 12, no. 7, pp. 1–18, 2020.

[2] T. R. Hwang, M. Kang, and H. Y. Jung, "Application of IoT and big data analytics to smart water systems," Sensors, vol. 21, no. 6, pp. 1–20, 2021.

[3] R. Kumar et al., "Smart water management using machine learning and IoT," Journal of Water Resources Planning and Management, vol. 146, no. 6, 2020.

[4] A. Ghaffarianhoseini et al., "Intelligent urban water management system using artificial intelligence," Smart Cities, vol. 3, no. 3, pp. 982–1002, 2020.

[5] A. Jain et al., "Machine learning approaches for urban water demand forecasting: a review," Environmental Modelling & Software, vol. 134, 2020.

[6] Y. Liu et al., "Smart water management: an overview," Journal of Cleaner Production, vol. 289, 2021.

[7] J. A. Pulido-Calvo and M. Gutierrez-Estrada, "Improved ARIMA models for water demand forecasting," Journal of Hydrology, vol. 414–415, pp. 290–300, 2012.

[8] M. Herrera et al., "Predictive models for forecasting hourly urban water demand," Journal of Hydrology, vol. 387, no. 1–2, pp. 141–150, 2010.

[9] J. Adamowski and C. Karapataki, "Comparison of multivariate regression and machine learning methods for urban water demand forecasting," Environmental Modelling & Software, vol. 36, pp. 141–151, 2012.

[10] Y. Gong, Q. Xu, and Z. Liu, "Optimization of pump operation using Random Forests and water demand prediction," Water Resources Management, vol. 33, pp. 1789–1802, 2019.

[11] W. Duan et al., "Hybrid LSTM model for multi-step water demand prediction," Water Supply, vol. 20, no. 8, pp. 2964–2975, 2020.

[12] N. Tao et al., "Water demand forecasting using LSTM neural network based on climatic and consumption data," Journal of Hydroinformatics, vol. 23, no. 2, pp. 234–248, 2021.

[13] A. Singh et al., "Urban water demand prediction incorporating weather data and consumer behavior," Applied Water Science, vol. 10, no. 9, pp. 1–13, 2020.

[14] H. Ghazal et al., "Forecasting urban water consumption using machine learning models and climate data," Sustainable Cities and Society, vol. 60, 2020.

[15] H. Fang, L. Li, and Y. Liu, "Smart city water distribution system using sensor analytics," Sensors, vol. 20, no. 9, 2020.

[16] K. Lee et al., "A review of anomaly detection in smart water grids using data-driven techniques," Smart Water, vol. 5, no. 2, 2020.

[17] D. Kim et al., "An intelligent water distribution management system integrating ML with SCADA," Environmental Engineering Science, vol. 38, no. 1, 2021.

[18] M. Wu and M. W. Hoffman, "Application of deep learning in water demand prediction," IEEE Trans. Industrial Informatics, vol. 17, no. 8, pp. 5640–5649, 2021.

[19] F. Zhang et al., "Time series forecasting of water consumption using deep learning and meteorological data," Water, vol. 13, no. 5, 2021.

[20] A. Singh and R. Sharma, "A reinforcement learning model for adaptive water distribution," Applied Soft Computing, vol. 110, 2021.

[21] M. Azari et al., "Big data analytics in water distribution networks: a systematic review," Water, vol. 12, no. 10, 2020.