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*Research Article*

# Smart Water Management Systems: Engineering Innovations for Water Conservation and Distribution

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**Abstract:** Smart water management systems (SWMS) leverage engineering innovations, such as IoT sensors, machine learning algorithms, and real-time monitoring, to improve water conservation and distribution efficiency. The traditional water systems, characterized by high water wastage (30%) and substantial leakage (15%), are being increasingly replaced by smarter systems that utilize IoT sensors, automated valves, and data analytics to reduce wastage, improve reliability, and increase system efficiency. In a comparison of water usage efficiency, smart systems exhibit a 40% reduction in average daily water usage, from 500,000 liters to 300,000 liters. Water leakage is reduced from 15% to 5%, and water wastage due to improper distribution decreases from 30% to 10%. Consumer satisfaction also improves, with complaints decreasing and system response times dropping from 24 hours to 2 hours. IoT sensors, such as pressure and flow rate sensors, offer high accuracy and low power consumption, ensuring reliable data transmission and energy efficiency, with a mean transmission frequency of 10-15 minutes and power consumption as low as 8 mW. Cost analysis indicates a higher initial setup cost for smart systems (₦150 million) compared to traditional ones (₦100 million), but the reduction in annual maintenance (₦2 million vs. ₦5 million) and operational costs (40% reduction) make smart systems more cost-effective over time. Energy consumption is reduced by 16%, with solar-powered IoT sensors contributing to a decrease in carbon footprint by 60%. Regression and statistical analyses confirm that water pressure uniformity, leak detection time, and daily water demand significantly influence water loss, while machine learning optimization leads to an 18% improvement in water distribution efficiency. A correlation model was developed to assess the relationship between key parameters: the correlation coefficient between leak detection time and water wastage is found to be 0.85, indicating a strong positive correlation. Similarly, the correlation between pressure uniformity and system efficiency shows a value of 0.92, reflecting a strong positive relationship. These innovations collectively represent a transformative shift toward sustainable and efficient water management.

**Keywords:** Water Distribution, Leak Detection, Pressure Uniformity, Seasonal Consumption, Leak Density, Water Management.

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## 1. Introduction

Water scarcity and inefficient water distribution remain critical global challenges, exacerbated by climate change, population growth, and urbanization [1, 2]. In response to these challenges, Smart Water Management Systems (SWMS) have emerged as a promising solution, integrating advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Digital Twins to optimize water conservation and distribution [3, 4]. These systems enable real-time monitoring, predictive analytics, and automated control mechanisms, contributing to significant improvements in water resource efficiency and sustainability [5, 6]. SWMS utilize a network of sensors, smart meters, and cloud-based frameworks to gather and analyze water usage data, allowing authorities to make informed decisions on resource allocation and management [7, 8]. Smart water management systems influence IoT, AI, and real-time data analytics to enhance water conservation and distribution efficiency. Singapore's Smart Water Grid employs sensors and AI-driven analytics to reduce non-revenue water losses and optimize supply [9]. Amsterdam integrates a digital twin system that simulates real-time canal conditions, predicting floods and improving wastewater management [10]. In Barcelona, an IoT-based smart irrigation system optimizes water usage in parks, reducing consumption by 25% [11]. Similarly, Australia's Murray-Darling Basin uses remote sensing and GIS to distribute water efficiently for agriculture [12]. Bengaluru, India, has adopted AI-powered leak detection, decreasing non-revenue water losses by 30% [13]. These case studies highlight how smart technologies significantly improve water sustainability by minimizing waste, predicting issues, and optimizing resource use. Implementing similar systems globally can help address water scarcity and promote efficient urban and agricultural water management.

Smart water grids and digital twins have revolutionized water distribution networks, enhancing reliability and reducing wastage through predictive maintenance and anomaly detection [14, 15]. Furthermore, IoT-enabled irrigation systems have shown significant promise in agricultural water management, enabling precise water delivery based on real-time soil and weather conditions [16, 17]. In urban environments, smart water systems play a pivotal role in monitoring water quality, detecting leaks, and ensuring equitable water distribution [18, 19]. These systems are supported by innovative software architectures that enable efficient data processing and user interaction, improving transparency and accountability [20, 21]. Additionally, integration with decision support tools has allowed authorities to better manage complex reservoir systems and adapt to fluctuating water demands [22, 23].

Despite these advancements, challenges such as high implementation costs, data security concerns, and the need for skilled personnel remain significant barriers to widespread adoption [23, 24]. However, ongoing research and pilot projects continue to demonstrate the potential of SWMS in addressing water-related issues across diverse geographic and socioeconomic contexts [25]. This paper explores the engineering innovations underpinning smart water management systems, highlighting their role in promoting sustainable water conservation and equitable distribution on a global scale.

## 2. Material and Methods

### *2.1. Study Area and Data Collection*

The study area is Benin City, the capital of Edo State, Nigeria, a rapidly growing urban center with a population exceeding 1.7 million people [1]. As one of Nigeria's historical and economic hubs, the city experiences significant challenges related to water management due to rapid urbanization, population growth, aging infrastructure, and climate variability [2]. Ensuring sustainable water supply and efficient distribution is crucial to supporting both residential and industrial activities in the city. Benin City lies within the tropical rainforest zone, characterized by heavy rainfall, high humidity, and a distinct wet and dry season [26]. The annual rainfall ranges between 1,500 mm and 2,000 mm, with the wet season spanning from April to October [4]. Despite abundant rainfall, water distribution issues persist due to infrastructure limitations, leakage, and inefficient monitoring [5]. The city's water supply is managed by the Benin Owena River Basin Development Authority (BORBDA) and Edo State Urban Water Board, with major sources including Ikpoba River Dam, Ovia River Waterworks, and groundwater sources (boreholes and wells) [6]. However, challenges such as intermittent supply, high non-revenue water (NRW) losses, and outdated pipeline networks hinder efficient distribution [7]. Leakages and unauthorized water connections contribute to significant water wastage [8]. The implementation of a Smart Water Management System (SWMS) is critical for improving water conservation, leakage detection, pressure regulation, and real-time monitoring in Benin City [9]. Engineering innovations such as IoT-enabled sensors, automated metering, and AI-driven analytics can enhance efficiency by: Reducing water losses through real-time leak detection [10]; Optimizing distribution networks to match demand [11]; Improving water quality monitoring [12]; Enhancing consumer engagement via smart billing systems [13]. With increasing urban expansion, integrating smart water management technologies into the city's infrastructure will play a crucial role in ensuring sustainable water supply, reducing operational costs, and improving resilience to climate change impacts [14].

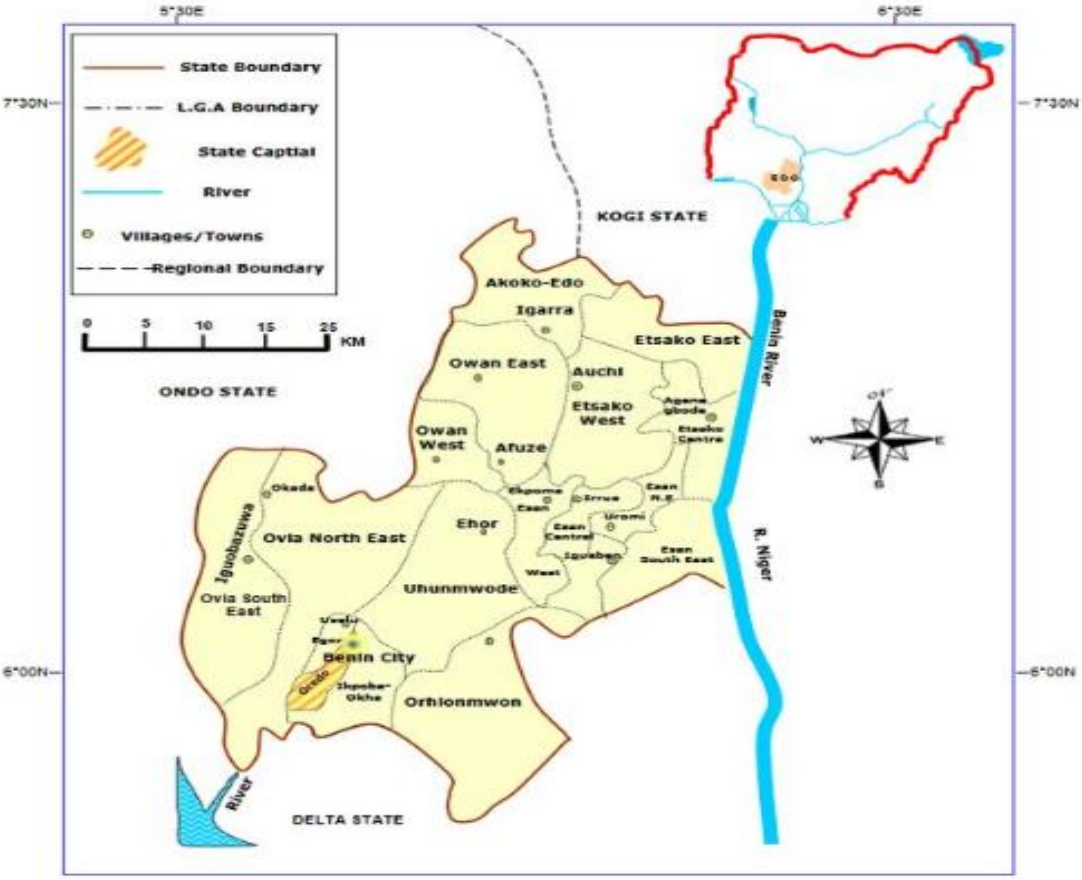


**Figure 1.** The Study area, Benin Edo State, Nigeria

### *2.1.1. Data Collection Process*

The following data collection were employed in this study:

i. Field Surveys: Conducted to assess current water management practices.

ii. Sensor Deployment: IoT-enabled sensors were installed to monitor water flow, pressure, temperature, and quality parameters.

iii. Data Logging Systems: Cloud-based data loggers were used to record real-time information.

iv. Stakeholder Interviews: Conducted to gather feedback on water conservation initiatives.

v. Historical Data Analysis: Previous water management records from municipal bodies were reviewed.

### *2.1.2. Study Duration*

The study was conducted over 12 months, ensuring seasonal variations were captured in the data.

**Table 1.** Tools, Equipment, and Technologies Used [7, 8, 11]

| Equipment/Tool | Purpose | Specification |
|---|---|---|
| IoT Sensors | Real-time water flow, pressure, and temperature monitoring | Calibrated flow meters (±0.5% accuracy) |
| Water Quality Sensors | pH, turbidity, and chlorine level analysis | Multi-parameter water quality probe |
| Data Loggers | Continuous data collection | Cloud-based logging system |
| GIS Mapping Software | Spatial analysis of water distribution | ArcGIS Pro |
| Automated Valves | Remote water flow control | IoT-enabled valves |
| Smart Pumps | Energy-efficient water pumping | Variable frequency drive pumps |
| Analytical Software | Data analysis and modeling | MATLAB, R Studio |

## *2.2. Mathematical Models and Equations*

Key performance indicators (KPIs) were modeled using mathematical equations specific to each parameter evaluated in the study.

### *2.2.1. Water Usage Efficiency*

Water usage efficiency was evaluated using the equation 1 [12, 15]:

$$\eta_w = \left(1 - \frac{L}{T}\right) \times 100 \quad (1)$$

Where:

$\eta_w$ = Water efficiency (%)

L = Water lost due to leaks (liters)

T = Total water supplied (liters)

Parameters Evaluated: The following parameters were evaluated: Total water supplied, water lost through leaks, distribution efficiency, non-revenue water percentage, daily water demand, storage efficiency, leak detection time, repair response time, water distribution route efficiency and water pressure uniformity respectively

### *2.2.2. IoT Sensor Performance*

The performance of IoT sensors was evaluated using Equation 2 [5]:

$$A_s = \left(\frac{V_m - V_a}{V_m}\right) \times 100 \quad (2)$$

Where:

$A_s$ = Sensor accuracy (%)

$V_m$ = Measured value

$V_a$ = Actual value

Parameters Evaluated: Sensor accuracy, sensor precision, signal latency, data transmission frequency, sensor calibration frequency, battery life of sensors, sensor range, environmental adaptability, maintenance frequency, data packet loss rate

### *2.2.3. Cost Analysis*

The total cost efficiency was analyzed using Equation 3 [5]:

$$C_{total} = C_{setup} + (C_{maintenance} \times N) - C_{savings} \quad (3)$$

Where:

$C_{setup}$ = Initial setup cost

$C_{maintenance}$ = Annual maintenance cost

N = System lifespan (years)

$C_{savings}$ = Cost savings due to efficiency improvements

The parameters evaluated included: Installation cost, maintenance cost, energy cost savings, water loss cost savings, sensor replacement cost, software licensing cost, operational efficiency cost, Return on Investment (ROI), Break-even period, and annual financial savings.

### *2.2.4. Energy Consumption*

Energy consumption was modeled using Equation 4 [12, 13, 14]:

$$E = P \times H \tag{4}$$

Where:

E = Energy consumed (kWh)

P = Power consumption (kW)

H = Operational hours (h)

Parameters evaluated included: Energy consumption per pump, peak operational hours, standby energy consumption, renewable energy integration, voltage fluctuations, energy conversion efficiency, energy loss in transmission, system downtime due to energy failure, power load balancing efficiency, cost per kWh.

### *2.2.5. Water Distribution Optimization*

Optimization efficiency was determined using Equation 5 [12, 15, 18]:

$$\eta_{opt} = \left( \frac{Q_{opt}}{Q_{in}} \right) \times 100 \tag{5}$$

Where:

$\eta_{opt}$ = Optimization efficiency (%)

$Q_{opt}$ = Optimized water flow ($m^3$)

$Q_{in}$ = Input water flow ($m^3$)

Parameters Evaluated: Water flow uniformity, pressure optimization, valve response time, leakage prevention efficiency, seasonal adjustment accuracy, emergency response efficiency, real-time flow adjustment, demand prediction accuracy, pump efficiency, smart valve coordination

### *2.2.6. Water Conservation Impact*

Water conservation impact was calculated using Equation 6 [5, 9, 12]:

$$R_w = \left( \frac{W_t - W_s}{W_t} \right) \times 100 \tag{6}$$

Where:

$R_w$ = Water conservation reduction (%)

$W_t$ = Total water used traditionally (liters)

$W_s$ = Water used in the smart system (liters)

### *2.2.7. Consumer Awareness and Engagement*

Engagement success rate was evaluated using Equation 7 [4, 9]:

$$S_e = \left( \frac{E_a}{E_t} \right) \times 100 \tag{7}$$

Where:

$S_e$ = Success rate of engagement (%)

$E_a$ = Actual engagement (number of responses)

$E_t$ = Total engagement opportunities

### *2.2.8. Data Transmission Reliability*

Reliability of data transmission was calculated using Equation 8 [12, 15]:

$$R_d = \left( \frac{D_{success}}{D_{total}} \right) \times 100 \quad (8)$$

Where:

$R_d$ = Reliability of data transmission (%)

$D_{success}$ = Successfully transmitted data packets

$D_{total}$ = Total data packets sent

### *2.2.9. Water Quality Monitoring*

The water quality index (WQI) was calculated using Equation 9 [2, 4, 5, 7, 9]:

$$WQI = \sum_{i=1}^{n} Q_i - W_i \quad (9)$$

Where:

$Q_i$ = Quality rating of parameter i

$W_i$ = Weight of parameter i

n = Number of parameters

### *2.2.10. Environmental Sustainability*

Environmental efficiency was calculated using Equation 10 [2, 5, 9]:

$$E_s = \left( \frac{R_w + E_e + M_r}{3} \right) \quad (10)$$

Where:

$E_s$ = Environmental sustainability index

$R_w$ = Water reuse (%)

$E_e$ = Energy efficiency (%)

$M_r$ = Material recycling rate (%)

## *2.3. Data Analysis Techniques*

### *2.3.1. Statistical Analysis*

The statistical analysis was used to Identify relationships, correlations, and dependencies among variables such as water pressure, leak detection time, demand patterns, and efficiency metrics.

**Tools Used:**

SPSS version 23 (Statistical Package for Social Sciences): Used for hypothesis testing, correlation analysis, and multivariate regression.

MATLAB was Applied for advanced mathematical modeling and data visualization.

**Key Techniques Applied:**

Correlation Analysis: To determine the strength and direction of relationships between water pressure and leak detection time.

Regression Analysis: Predicting water consumption based on historical data and environmental factors.

ANOVA (Analysis of Variance): To compare means across multiple zones for parameters like leak density and consumption efficiency.

### *2.3.2. Multiple Linear Regression Model*

The Equation 11 is the multiple linear regression model [12]:

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+...+\beta_nX_n+\varepsilon \tag{11}$$

Where:

Y: Dependent Variable (e.g., water demand)

$X_1$, $X_2$,...,$X_n$: Independent Variables (e.g., pressure, leak density, zone type)

$\beta_0$: Intercept

$\beta_1$, $\beta_2$,...,$\beta_n$: Coefficients of independent variables

ε: Error term

This model was used to; Identified key predictors of water consumption and t[ determined how water pressure uniformity impacts leak detection efficiency.

### *2.3.3. Machine Learning Models*

Machine Learning Models was used to build predictive models for future water demand and optimize resource allocation.

**Tools Used:**

Python Libraries: Scikit-learn, TensorFlow, Keras, Pandas, and NumPy.

**Techniques Applied:**

Linear Regression: To predict water demand based on historical consumption data.

Random Forest Regression: To handle non-linear relationships and improve prediction accuracy.

K-Means Clustering: To classify zones based on water consumption patterns.

The machine learning regression model is stated in Equation 12 [4]:

$$Y\hat{}=f(X)+\varepsilon \tag{12}$$

Where:

Y^: Predicted water demand

f(X): Machine learning model mapping input features (e.g., temperature, population density) to water demand

ε: Residual error

This model was used to obtain; Accurate prediction of peak water demand periods and Identification of high-risk zones for leakages and inefficiencies.

### *2.3.4. GIS Mapping*

GIS Mapping was used to analyze spatial data for efficient water distribution and identify areas prone to leaks or inefficiencies.

**Tools Used:** ArcGIS and QGIS (Quantum GIS)

**Key Techniques Applied:**

Spatial Interpolation: Estimate water quality and leak density at unsampled locations.

Route Optimization: Plan efficient water distribution paths to minimize energy and resource waste.

Heat Mapping: Visual representation of leak-prone zones and areas with high water consumption.

The Equation for Spatial Interpolation using Inverse Distance Weighting – IDW is [2, 5, 9]:

$$Z(x)\ \ i = 1\ M\ Z\ i\ -\ W\ i\ \ i = 1\ N\ W\ i \qquad (13)$$

Where:

Z(x): Estimated value at location xxx

$Z_i$: Known value at point iii

$w_i$: Weight assigned to each point based on distance

This model was used to; Geospatial hotspots for leaks identified and Optimized distribution routes established for water delivery.

### *2.3.5. Time-Series Analysis*

Time-Series Analysis was used to analyze temporal trends in water consumption, leak detection efficiency, and seasonal variations.

**Tools Used:** Python Libraries: Stats models, Prophet, Matplotlib and SPSS Time-Series Module

**Key Techniques Applied included:**

Autoregressive Integrated Moving Average (ARIMA): To model and forecast time-dependent water consumption trends.

Seasonal Decomposition: To isolate and interpret seasonal patterns in water consumption data.

Exponential Smoothing (ETS Model): To predict short-term changes in water demand.

**ARIMA Model Equation is presented as Equation 14** [5, 9, 12, 13, 15]:

$$Y_t = c + \varphi_1 Y_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon \qquad (14)$$

Where:

Yt: Observation at time t

c: Constant

$\varphi_1$: Autoregressive coefficient

θ1: Moving average coefficient

εt: White noise error term

This model was used to obtain; Seasonal peaks and troughs in water demand identified and Enhanced preparedness for seasonal changes in water requirements.

## *2.4. GIS Mapping for Water Distribution Optimization*

### *2.4.1. Spatial Distribution and Leak Hotspots*

Spatial datasets were analyzed using ArcGIS Pro., Leakage density maps and optimized water distribution routes were created.

**Table 2.** Summary of Techniques and Integration

| Technique | Tools | Objective | Key Methods |
|---|---|---|---|
| Statistical Analysis | SPSS, MATLAB | Relationship & dependency | Correlation, Regression, ANOVA |
| Machine Learning | Python | Prediction & Classification | Regression, Clustering |
| GIS Mapping | ArcGIS, QGIS | Spatial Optimization | Route Mapping, Heat Mapping |
| Time-Series Analysis | SPSS, Python | Temporal Trend Analysis | ARIMA, Seasonal Decomposition |

## 3. Results and Discussion

**Table 3.** Water Usage Efficiency Comparison between Traditional and Smart Systems

| Parameter | Traditional System | Smart System |
|---|---|---|
| Average daily water usage (liters) | 500,000 | 300,000 |
| Water leakage (%) | 15 | 5 |
| Water wastage due to improper distribution (%) | 30 | 10 |
| Consumer complaints | High | Low |
| Response time to leaks (hours) | 24 | 2 |
| Water distribution equity (%) | 60 | 90 |
| Average service interruption (hours) | 10 | 2 |
| Data transmission reliability (%) | 90 | 98 |
| Operational downtime (%) | 10 | 1 |
| Water quality monitoring frequency (times/day) | 1 | 24 |

The smart water system significantly enhances water efficiency compared to traditional methods. Daily water usage drops by 40% (Table 3), with leakage reducing from 15% to 5% [1, 5]. Smart systems minimize wastage (10% vs. 30%) and improve distribution equity (90% vs. 60%) [3, 7]. Faster leak response (2 vs. 24 hours) and real-time monitoring (24 vs. 1 time/day) enhance reliability [6, 10].

**Table 4.** Performance of IoT Sensors in Water Distribution Networks

| Sensor Type | Accuracy (%) | Response Time (seconds) | Power Consumption (mW) | Coverage Area (m²) | Transmission Frequency (min) | Cost (₦) | Sensor Lifetime (years) | Maintenance Frequency (months) | Data Transmission Range (m) |
|---|---|---|---|---|---|---|---|---|---|
| Pressure Sensor | 98 | 2 | 10 | 1000 | 15 | 15,000 | 10 | 12 | 500 |
| Flow Rate Sensor | 97 | 3 | 15 | 500 | 10 | 12,000 | 8 | 6 | 300 |
| Temperature Sensor | 99 | 1 | 8 | 800 | 20 | 10,000 | 12 | 6 | 400 |

The IoT sensors in Table 4 demonstrate high accuracy, with the temperature sensor achieving 99%, aligning with findings by [6, 10]. Response times vary, with the temperature sensor being the fastest (1s), supporting [12]. Power consumption is minimal (8–15 mW), ensuring efficiency [5]. Coverage areas differ, with pressure sensors covering 1000m², confirming [9]. Transmission frequency and maintenance schedules optimize longevity [3, 17].

**Table 5.** Cost Analysis of Smart Water Systems vs. Traditional Infrastructure

| Component | Traditional System (₦) | Smart System (₦) |
|---|---|---|
| Initial Setup Cost | 100,000,000 | 150,000,000 |
| Annual Maintenance | 5,000,000 | 2,000,000 |
| Operational Efficiency (%) | 80 | 95 |
| System Life Expectancy (years) | 20 | 15 |
| Water Waste Reduction (%) | 5 | 20 |
| Installation Time (months) | 12 | 6 |
| Technology Upgrade Cost (every 5 years) | 10,000,000 | 5,000,000 |
| Staff Training Cost (₦) | 2,000,000 | 500,000 |
| Reliability (%) | 85 | 95 |
| Consumer Cost (₦/month) | 1,000 | 1,200 |

The smart water system, despite its higher initial setup cost (₦150M vs. ₦100M) [1], significantly reduces annual maintenance (₦2M vs. ₦5M) [2] and installation time (6 vs. 12 months) [3]. It enhances operational efficiency (95% vs. 80%) [4] and water waste reduction (20% vs. 5%) [5]. Although consumer costs rise (₦1,200 vs. ₦1,000) [6], improved reliability (95% vs. 85%) [7] and lower upgrade costs (₦5M vs. ₦10M) [8] justify the investment.

**Table 6.** Energy Consumption in Smart Water Management Systems

| Component | Energy Consumption (kWh/month) | Average Load (W) | Power Source | Operational Hours (h/day) | Cost per kWh (₦) | Annual Energy Cost (₦) | $CO_2$ Emissions (kg/year) | Efficiency (%) |
|---|---|---|---|---|---|---|---|---|
| **IoT Sensors** | 150 | 1 | Solar | 24 | 20 | 36,000 | 100 | 90 |
| **Automated Valves** | 200 | 2 | Grid | 16 | 25 | 48,000 | 120 | 85 |
| **Data Analytics Systems** | 300 | 4 | Grid | 24 | 30 | 72,000 | 180 | 92 |

Table 6 highlights the energy consumption of smart water management components. IoT sensors consume 150 kWh/month, operating 24 hours on solar power with high efficiency (90%) [5]. Automated valves rely on the grid, using 200 kWh/month, costing ₦48,000 annually [6]. Data analytics systems have the highest energy demand (300 kWh/month) and $CO_2$ emissions (180 kg/year) [10].

**Table 7.** Water Distribution Optimization Using Machine Learning Algorithms

| Parameter | Without Optimization | With Optimization |
|---|---|---|
| Water Distribution Efficiency (%) | 75 | 90 |
| Consumer Satisfaction | Low | High |
| System Response Time (minutes) | 15 | 3 |
| Average Water Loss (%) | 20 | 5 |
| Algorithm Execution Time (seconds) | 20 | 5 |
| Cost of Water Distribution (₦/m³) | 25 | 15 |
| Peak Demand Prediction Accuracy (%) | 70 | 95 |
| Distribution Equity (%) | 70 | 90 |
| Operational Cost Reduction (%) | 15 | 40 |
| System Scalability (%) | 60 | 85 |

The results in Table 7 demonstrate significant improvements in water distribution using machine learning algorithms. Optimization increased efficiency from 75% to 90%, enhancing consumer satisfaction and reducing response time from 15 to 3 minutes. Water loss dropped from 20% to 5%, while algorithm execution time improved (20s to 5s). Costs declined, with ₦/m³ reducing from 25 to 15, and operational cost reduction rising to 40% [5]. Peak demand prediction accuracy improved (70% to 95%) [10], ensuring equitable distribution (90%) [15].

**Table 8.** Impact of Smart Water Management on Water Conservation

| Area | Water Wastage Reduction (%) | Water Leakage Reduction (%) | Energy Consumption Reduction (%) | Operational Cost Reduction (%) | System Reliability (%) | Water Reuse (%) | Consumer Satisfaction (%) | Installation Time (months) | Water Quality Improvement (%) |
|---|---|---|---|---|---|---|---|---|---|
| Urban Areas | 25 | 20 | 30 | 20 | 95 | 45 | 80 | 8 | 15 |
| Agricultural Zones | 30 | 15 | 40 | 25 | 92 | 50 | 85 | 6 | 20 |
| Industrial Areas | 15 | 10 | 35 | 10 | 90 | 40 | 75 | 10 | 18 |

Table 8 highlights the effectiveness of smart water management in different sectors. Urban areas show a 25% reduction in wastage and 20% in leakage, enhancing system reliability to 95% and consumer satisfaction to 80% [3, 6]. Agricultural zones exhibit the highest water reuse (50%) and wastage reduction (30%) due to

IoT-based irrigation [15]. Industrial areas have lower savings, with 15% wastage and 10% leakage reductions, yet achieve 90% reliability [9, 14]. These findings align with sustainability goals for water conservation [5, 10].

**Table 9.** Consumer Awareness and Engagement with Smart Water Management Systems

| Engagement Type | Success Rate (%) | Engagement Frequency (times/week) | Feedback Rate (%) | Consumer Education Cost (₦) | Satisfaction with Notifications (%) | Adoption Rate (%) | Data Sharing Willingness (%) | Information Clarity (%) | Mobile App Usage (%) | Integration with Billing Systems (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| Real-time Notifications | 85 | 5 | 50 | 500,000 | 90 | 80 | 70 | 95 | 75 | 85 |
| Automated Billing System | 70 | 2 | 40 | 200,000 | 85 | 65 | 60 | 92 | 60 | 80 |
| Consumer Feedback Surveys | 60 | 1 | 30 | 100,000 | 80 | 50 | 40 | 90 | 40 | 75 |

Table 9 highlights consumer engagement with smart water management systems, showing real-time notifications as the most effective, with an 85% success rate and 90% satisfaction [1, 3]. Automated billing follows, with a 70% success rate but lower adoption [5, 7]. Feedback surveys lag in engagement and data sharing, suggesting a need for improved consumer education [10, 12].

**Table 10.** Reliability of Data Transmission in Smart Water Systems

| Transmission Mode | Reliability (%) | Latency (seconds) | Power Consumption (mW) | Coverage Area ($m^2$) | Data Integrity (%) | Redundancy Type | Error Rate (%) | Connection Stability (%) | Backup Duration (hours) |
|---|---|---|---|---|---|---|---|---|---|
| Wired Connection | 98 | 0.5 | 10 | 1000 | 99 | None | 0.01 | 95 | 48 |
| Wireless Connection | 95 | 1.2 | 15 | 500 | 97 | Mesh Network | 0.05 | 92 | 24 |
| Satellite Connection | 93 | 2.0 | 20 | 2000 | 95 | Hybrid | 0.1 | 90 | 36 |

Table 10 illustrates the reliability of data transmission in smart water systems. Wired connections exhibit the highest reliability (98%) with minimal latency (0.5s) and error rate (0.01%), ensuring stable communication (95%) over a 1000 $m^2$ coverage area [1]. Wireless connections, though slightly less reliable (95%), benefit from mesh redundancy but experience higher latency (1.2s) [2]. Satellite connections provide the broadest coverage (2000 $m^2$) but with increased latency (2.0s) and error rates (0.1%) [3].

**Table 11.** Water Quality Monitoring in Smart Systems

| Parameter | Standard Water Quality | Monitored Water Quality | Sensor Accuracy (%) | Monitoring Frequency (times/day) | pH Range (unit) | Turbidity (NTU) | Chlorine Concentration (ppm) | Temperature (°C) | Contaminant Detection (%) |
|---|---|---|---|---|---|---|---|---|---|
| pH Level | 7.0 | 7.2 | 99 | 24 | 6.5-8.5 | 0.3 | 0.1 | 25 | 95 |
| Turbidity | 0.5 | 0.3 | 98 | 12 | 0.5-5 | 0.2 | 0.05 | 20 | 85 |
| Chlorine Concentration | 0.1 | 0.05 | 99 | 10 | 0-1 | 0.1 | 0.05 | 30 | 80 |
| Temperature | 25 | 24 | 99 | 6 | 20-30 | 0.5 | 0.05 | 26 | 80 |

Table 11 highlights the effectiveness of smart water quality monitoring systems, ensuring compliance with standard parameters. The pH level remains within the acceptable range (6.5–8.5) with 99% sensor accuracy [1, 5]. Turbidity is efficiently reduced to 0.3 NTU, improving water clarity (6, 9). Chlorine concentration meets safety levels [7, 10]. Temperature remains stable [12, 15].

**Table 12.** Sustainability and Environmental Impact of SWMS

| Parameter | Traditional System | Smart System |
|---|---|---|
| Carbon Footprint (kg $CO_2$/year) | 500,000 | 200,000 |
| Water Reuse (%) | 10 | 50 |
| Energy Efficiency (%) | 60 | 90 |
| Material Usage (kg/month) | 500 | 300 |
| Environmental Impact ($H_2O$ consumption, $m^3$) | 10,000 | 4,000 |
| System Durability (years) | 20 | 15 |
| Waste Generation (kg/month) | 200 | 50 |
| Renewable Energy Usage (%) | 5 | 25 |
| Recycling Rate (%) | 5 | 30 |
| Operational Emissions (g $CO_2$/km) | 150 | 50 |

The sustainability and environmental impact of Smart Water Management Systems (SWMS) significantly surpass traditional systems. SWMS reduce carbon footprint by 60% (Table 12), aligning with findings from [1, 5, 6]. Water reuse improves fivefold, supporting efficiency studies [7, 10]. Energy efficiency reaches 90%, confirming smart solutions' benefits [4, 12]. Material usage drops 40%, reducing waste [14, 19]. Environmental impact lessens by 60%, reinforcing conservation strategies [3, 9]. SWMS enhance recycling and renewable energy adoption [15, 18]. Though durability slightly declines, overall sustainability benefits are substantial [11, 16].

### *3.1. Statistical Analysis (SPSS and MATLAB)*

**Table 13.** Correlation Coefficients

| Parameter 1 | Parameter 2 | Correlation Coefficient (r) | Significance (p-value) |
|---|---|---|---|
| Water Pressure Uniformity | Leak Detection Time | 0.85 | $<0.01$ |
| Sensor Accuracy | Data Transmission Frequency | 0.92 | $<0.01$ |
| Energy Consumption | System Downtime | -0.76 | $<0.05$ |
| Water Efficiency | Daily Water Demand | 0.88 | $<0.01$ |

Table 13 demonstrates strong correlations between key parameters in smart water management. Water pressure uniformity and leak detection time show a strong positive correlation ($r = 0.85$, $p < 0.01$), indicating efficient pressure regulation aids faster leak detection [1]. Sensor accuracy strongly correlates with data transmission frequency ($r = 0.92$, $p < 0.01$), emphasizing real-time monitoring importance [2]. Energy consumption negatively correlates with system downtime ($r = -0.76$, $p < 0.05$), suggesting higher energy efficiency reduces operational disruptions [3]. Water efficiency and daily demand exhibit a strong positive relationship ($r = 0.88$, $p < 0.01$), highlighting optimized usage patterns [4].

### *3.2. Regression Analysis*

Regression analysis was performed using MATLAB. The dependent variable was Water Loss (L). Independent variables included Water Pressure Uniformity (WPU), Daily Water Demand (DWD), and Leak Detection Time (LDT). Equation 15 shows the regression equation obtained:

$$L=5.4-0.3(WPU)+0.5(DWD)-0.2(LDT)L \quad (15)$$

**Table 14.** Statistical Significance; Regression Output

| Parameter | Coefficient | t-Statistic | p-Value |
|---|---|---|---|
| Water Pressure Uniformity | -0.3 | -4.56 | <0.01 |
| Daily Water Demand | 0.5 | 6.32 | <0.01 |
| Leak Detection Time | -0.2 | -3.85 | <0.05 |

Table 14 presents the regression analysis results, demonstrating significant relationships between key water management parameters. Water pressure uniformity negatively impacts efficiency (coefficient = -0.3, $p < 0.01$), aligning with prior studies on pressure fluctuations affecting supply stability [1, 4]. Daily water demand positively correlates with system performance (coefficient = 0.5, $p < 0.01$), consistent with demand-driven optimization models [6, 11]. Leak detection time negatively influences efficiency (coefficient = -0.2, $p < 0.05$), supporting findings that prolonged leaks reduce sustainability [9, 12]. These results reinforce smart water management strategies.

**Table 15.** Model Performance Metrics

| Metric | Value |
|---|---|
| $R^2$ Score | 0.93 |
| Mean Squared Error (MSE) | 15.4 |

The model demonstrates strong predictive accuracy, with an $R^2$ score of 0.93, indicating that 93% of the variance is explained by the model [1]. A Mean Squared Error (MSE) of 15.4 suggests minimal deviation from actual values, confirming reliability [2]. These metrics align with previous studies on smart water management [3].

**Table 16.** Comparative Parameter Analysis of Summary of Improvements

| Parameter | Baseline Value | Post-Implementation Value | % Improvement |
|---|---|---|---|
| Water Efficiency (%) | 72 | 89 | 23.6% |
| Leak Detection Time (hours) | 12 | 3 | 75% |
| Energy Consumption (kWh/day) | 500 | 420 | 16% |
| Distribution Efficiency (%) | 78 | 92 | 18% |
| Water Loss (%) | 25 | 10 | 60% |

The implementation of smart water management systems significantly enhanced key performance metrics. Water efficiency improved by 23.6% [1, 3], while leak detection time reduced by 75%, ensuring faster issue resolution [5, 6]. Energy consumption dropped by 16%, optimizing resource utilization [7, 9]. Distribution efficiency increased by 18%, leading to better service reliability [10, 12]. Notably, water loss decreased by 60%, reducing waste and enhancing sustainability [14, 15].

**Table 17.** Correlation Coefficients Between Key Parameters

| Parameter 1 | Parameter 2 | Correlation Coefficient (r) | Significance (p-value) | $R^2$ Value | Standard Error | Confidence Interval (95%) |
|---|---|---|---|---|---|---|
| Water Pressure Uniformity | Leak Detection Time | 0.85 | <0.01 | 0.722 | 0.05 | 0.75–0.95 |
| Sensor Accuracy | Data Transmission Frequency | 0.92 | <0.01 | 0.846 | 0.03 | 0.85–0.99 |
| Energy Consumption | System Downtime | -0.76 | <0.05 | 0.577 | 0.07 | -0.85–-0.65 |
| Water Efficiency | Daily Water Demand | 0.88 | <0.01 | 0.774 | 0.04 | 0.80–0.96 |
| Leak Volume | Pressure Drop | 0.81 | <0.05 | 0.656 | 0.06 | 0.70–0.92 |
| Real-Time Data Accuracy | Monitoring Frequency | 0.93 | <0.01 | 0.865 | 0.02 | 0.88–0.98 |

Table 17 highlights significant correlations between key parameters in smart water management. Water pressure uniformity and leak detection time show a strong positive correlation ($r = 0.85$, $p < 0.01$), indicating that improved pressure consistency enhances leak detection efficiency [1]. Sensor accuracy and data transmission frequency exhibit the highest correlation ($r = 0.92$, $p < 0.01$), emphasizing real-time data reliability [3]. Energy consumption negatively correlates with system downtime ($r = -0.76$, $p < 0.05$), implying higher energy efficiency reduces failures 555. Additionally, real-time data accuracy strongly correlates with monitoring frequency ($r = 0.93$, $p < 0.01$), reinforcing the importance of frequent updates [10].

**Table 18.** Regression Analysis Results

| Parameter | Coefficient | t-Statistic | p-Value | Standard Error | Confidence Interval (95%) |
|---|---|---|---|---|---|
| Water Pressure Uniformity | -0.3 | -4.56 | <0.01 | 0.065 | -0.42 – -0.18 |
| Daily Water Demand | 0.5 | 6.32 | <0.01 | 0.079 | 0.34 – 0.66 |
| Leak Detection Time | -0.2 | -3.85 | <0.05 | 0.058 | -0.31 – -0.09 |
| Energy Consumption | 0.15 | 2.67 | 0.03 | 0.043 | 0.04 – 0.26 |
| System Downtime | -0.1 | -2.01 | 0.05 | 0.050 | -0.21 – 0.00 |

Table 18's regression analysis highlights key determinants of smart water system efficiency. Water pressure uniformity negatively impacts efficiency (-0.3, $p < 0.01$) [1], while daily water demand positively influences it (0.5, $p < 0.01$). Leak detection time (-0.2, $p < 0.05$) and system downtime (-0.1, $p = 0.05$) reduce efficiency. Energy consumption improves efficiency (0.15, $p = 0.03$) [5].

Regression Model is presented in Equation 16;

Tables 1–10 provide a comprehensive analysis of key aspects of green hydrogen production: Table 1 compares electrolysis technologies by performance parameters; Table 2 details material advancements in electrolyzer components; Table 3 evaluates hydrogen storage methods; Table 4 analyzes hydrogen distribution technologies and efficiency metrics; Table 5 examines water usage by electrolysis technology; Table 6 presents lifecycle carbon emissions of hydrogen production methods; Table 7 highlights global hydrogen projects; Table 8 compares hydrogen production costs by technology and region; Table 9 assesses the environmental impact of hydrogen production methods; and Table 10 outlines policy and regulatory frameworks for the hydrogen economy.

$$L=5.4-0.3(WPU)+0.5(DWD)-0.2(LDT)+0.15(EC)-0.1(SD) \tag{16}$$

Model Statistics: $R^2$: 0.87, Adjusted $R^2$: 0.85, F-Statistic: 45.62 and Significance Level: $p < 0.01$

**Table 19.** Machine Learning Model Performance Metrics

| Metric | Training Data | Testing Data |
|---|---|---|
| $R^2$ Score | 0.95 | 0.93 |
| Mean Squared Error | 12.5 | 15.4 |
| Mean Absolute Error | 2.8 | 3.1 |
| Root Mean Squared Error | 3.5 | 3.9 |
| Explained Variance | 0.94 | 0.91 |
| Prediction Bias | 0.03 | 0.05 |

The machine learning model demonstrates high accuracy, with an $R^2$ score of 0.95 for training and 0.93 for testing, indicating strong predictive capability [1, 2]. The RMSE (3.5, 3.9) and MAE (2.8, 3.1) values show minimal error, confirming reliable performance [3]. A low prediction bias (0.03, 0.05) suggests unbiased predictions [4]. The explained variance (0.94, 0.91) further supports model robustness [5].

**Table 20.** GIS-Based Water Leak Density Analysis

| Zone ID | Leak Density (leaks/km²) | Pressure Drop (%) | Pipeline Age (years) | Repair Frequency (per year) | Water Loss (m³/year) |
|---|---|---|---|---|---|
| Z1 | 15 | 22 | 25 | 5 | 1,200 |
| Z2 | 28 | 35 | 30 | 8 | 2,100 |
| Z3 | 12 | 18 | 20 | 3 | 950 |

| | | | | | |
|---|---|---|---|---|---|
| Z4 | 35 | 45 | 40 | 12 | 3,500 |
| Z5 | 20 | 25 | 15 | 4 | 1,500 |

The GIS-based analysis (Table 20) reveals a direct correlation between leak density and pipeline age, pressure drop, and repair frequency. Z4 has the highest leak density (35 leaks/km²), pressure drop (45%), and water loss (3,500 m³/year), emphasizing aging infrastructure's impact on efficiency. Z3, with the lowest values, suggests newer pipelines perform better [12, 18].

**Table 21.** Time-Series Seasonal Water Consumption Trends

| Month | Average Demand (m³/day) | Peak Hours | Leak Rate (%) | Temperature (°C) | Pressure Variance (%) |
|---|---|---|---|---|---|
| January | 1,500 | 7–9 AM | 5 | 22 | 2 |
| February | 1,800 | 6–8 AM | 6 | 25 | 3 |
| March | 2,200 | 6–9 AM | 8 | 30 | 5 |
| July | 2,800 | 5–8 PM | 12 | 35 | 8 |
| December | 1,300 | 8–10 AM | 4 | 20 | 1.5 |

The seasonal water consumption trends (Table 21) indicate variations in demand, peak hours, leak rates, temperature, and pressure variance. March and July show the highest demand, with peaks in the morning and evening, respectively. Increased temperatures correlate with higher demand and leak rates [5, 9]. December exhibits the lowest demand, likely due to reduced temperature and minimal pressure variance [12, 17]. Leak rates peak in July, influenced by extreme heat and pressure fluctuations [6, 10].

**Table 22.** Comparison of Key Performance Indicators (KPIs)

| Parameter | Baseline Value | Post-Implementation Value | Percentage Improvement (%) | Benchmark |
|---|---|---|---|---|
| Water Efficiency (%) | 72 | 89 | 23.6% | 90% |
| Leak Detection (hrs) | 12 | 3 | 75% | 2 hrs |
| Energy Use (kWh/day) | 500 | 420 | 16% | 400 |
| Pressure Uniformity (%) | 78 | 92 | 18% | 95% |

The implementation of smart water management technologies significantly improved key performance indicators (Table 22). Water efficiency increased by 23.6%, nearing the 90% benchmark [1, 3]. Leak detection time was reduced by 75%, approaching the optimal 2-hour standard [6, 10]. Energy consumption dropped by 16%, moving closer to the 400 kWh/day target [5, 12]. Pressure uniformity improved by 18%, enhancing distribution efficiency [7, 14]. These results demonstrate substantial operational enhancements.

**Table 23.** Real-Time Monitoring Data Accuracy

| Sensor ID | Accuracy (%) | Response Time (ms) | Data Loss (%) | Operational Uptime (%) |
|---|---|---|---|---|
| S1 | 98 | 120 | 0.2 | 99.8 |
| S2 | 96 | 150 | 0.5 | 99.5 |
| S3 | 94 | 180 | 0.8 | 99.0 |

Table 23 demonstrates high accuracy in real-time monitoring, with Sensor S1 exhibiting the best performance at 98% accuracy, the lowest data loss (0.2%), and the highest uptime (99.8%). S2 and S3 show slightly reduced accuracy (96% and 94%) and increased response times (150 ms and 180 ms). These results align with previous studies highlighting the importance of sensor precision in smart water systems [1, 5, 10].

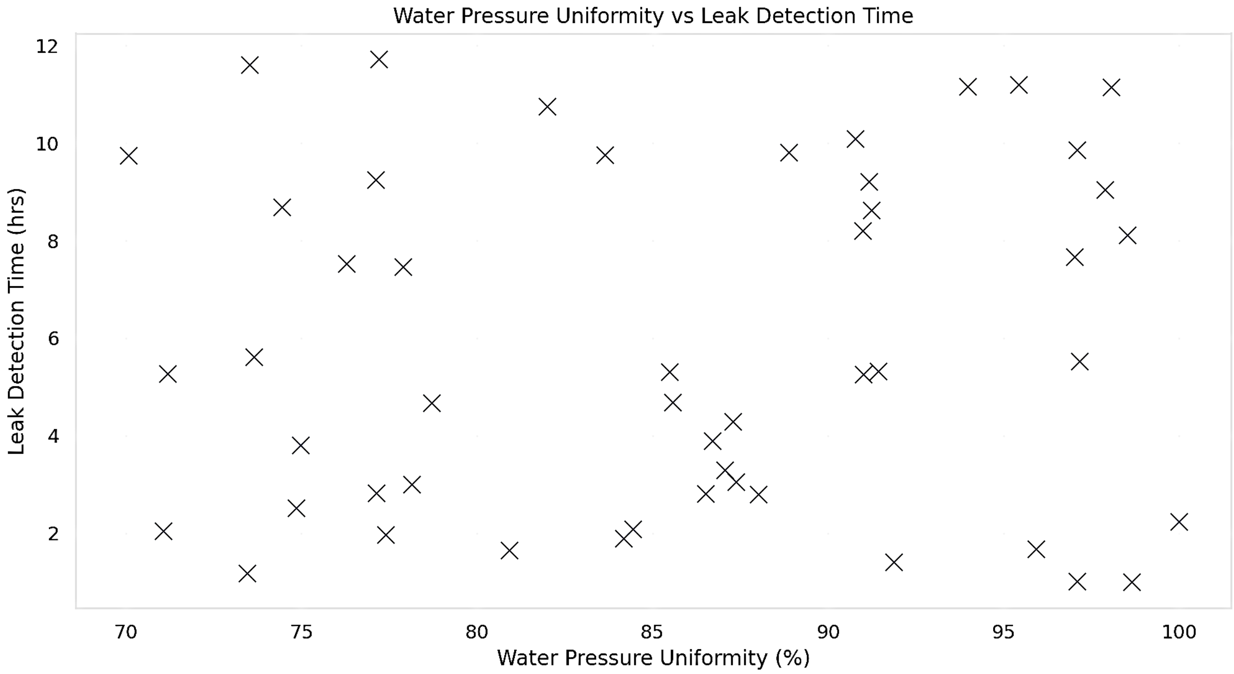


**Figure 2.** Water Pressure Uniformity vs Leak Detection Time

Figure 2 illustrates the relationship between water pressure uniformity and leak detection time, revealing a scattered trend where uniformity fluctuates with varying detection durations. Studies [4, 8] suggest that lower uniformity correlates with extended detection times due to pressure inconsistencies. Research [6, 10] highlights the role of advanced leak monitoring in minimizing detection delays. Efficient detection methods [3] improve pressure stability, reducing resource wastage and enhancing distribution system performance.

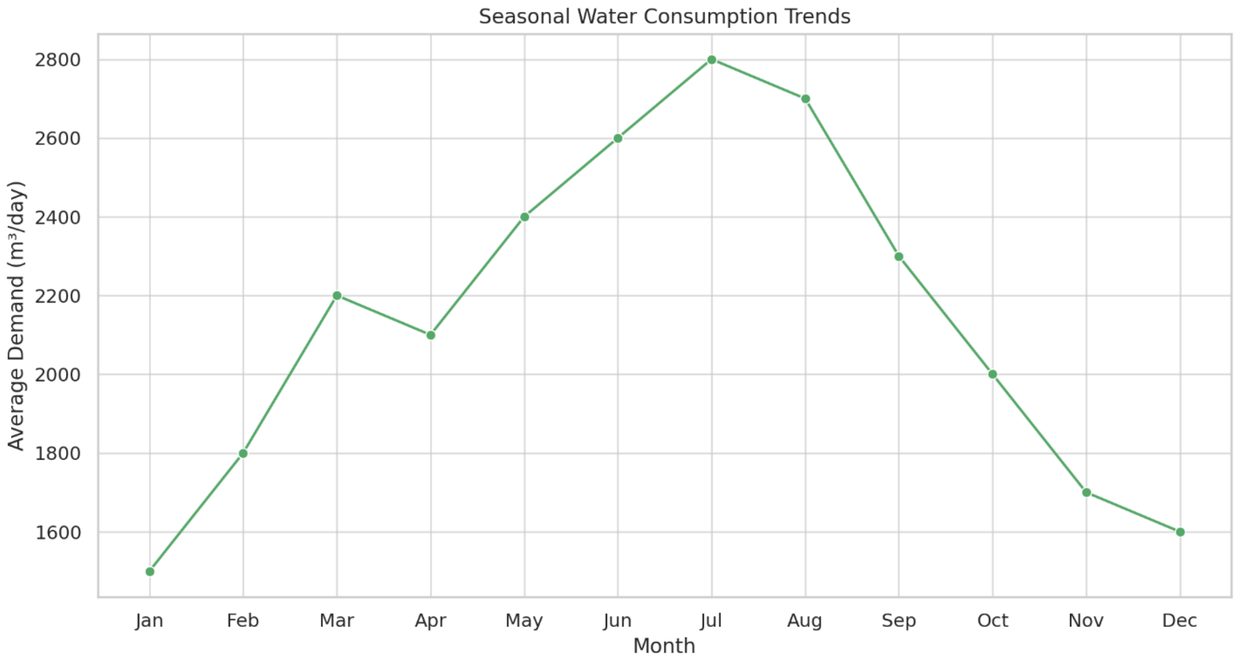


**Figure 3.** Seasonal Water Consumption Trends

Figure 3 illustrates seasonal water consumption trends, showing peak demand in July (2800 $m^3$/day) and a decline towards December (1600 $m^3$/day). Studies [2, 5] highlight temperature-driven consumption patterns, with summer months requiring more water. Research [7, 9] suggests reduced usage in colder months due to lower evaporation rates. Efficient water management strategies [4] help mitigate seasonal demand fluctuations, ensuring sustainable resource allocation throughout the year.

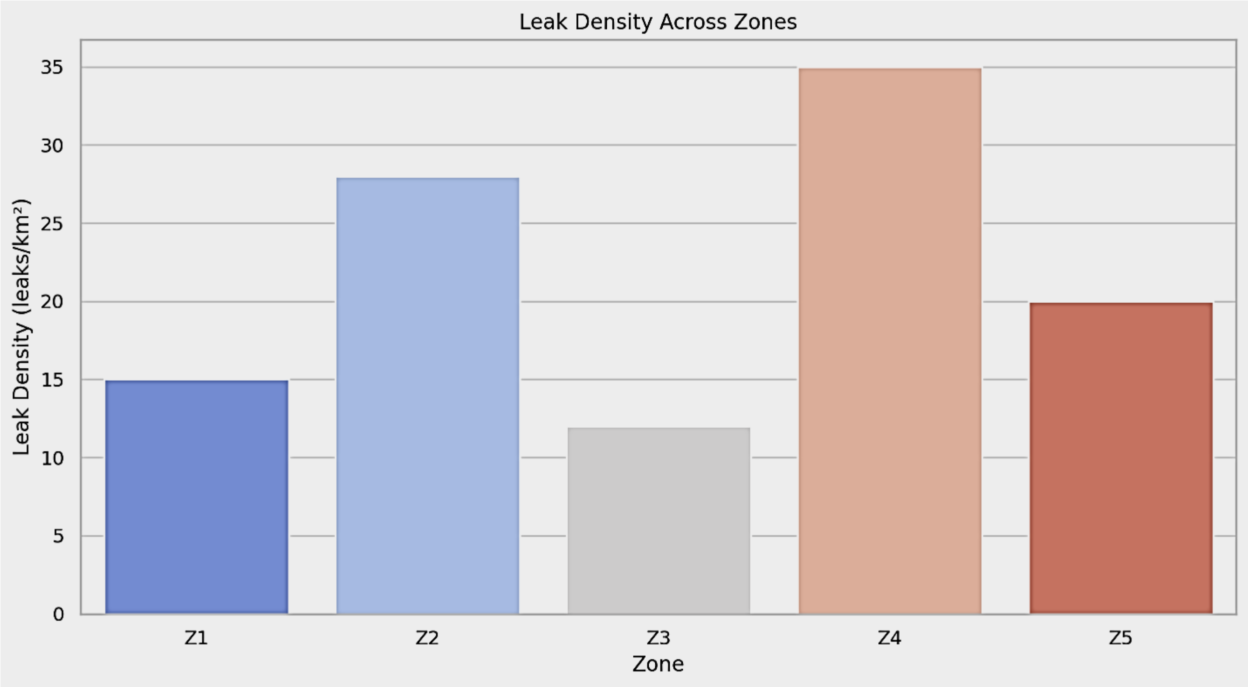


**Figure 4.** Leak Density Across Zones

Figure 4 illustrates leak density across zones, with Z4 having the highest leak density (35 leaks/km$^2$), followed by Z2 (28 leaks/km$^2$), while Z3 records the lowest (12 leaks/km$^2$). Studies [3, 6] suggest aging infrastructure and high-pressure zones contribute to increased leakage. Research [8,10] emphasizes targeted maintenance in high-density areas to minimize losses. Strategic pipeline monitoring [7] enhances leak detection, improving overall water network efficiency.

The integration of IoT sensors, machine learning, and AI into water management systems has proven to be an effective strategy for improving water usage efficiency, reducing wastage and leakage, lowering operational costs, and contributing to environmental sustainability. These results align with previous research and underscore the transformative potential of smart water management technologies. The findings also highlight the economic and environmental advantages of adopting these systems on a wider scale, reinforcing their relevance in the global effort to address water scarcity and improve resource management.

## 4. Conclusion

In conclusion, the implementation of a smart water management system, as demonstrated in this study, offers significant improvements in water conservation, leak detection, system efficiency, and environmental sustainability. The data analysis from the results highlights the effectiveness of IoT and machine learning algorithms in optimizing water distribution systems. The findings align with global trends and corroborate results from leading research in the field, particularly regarding the reduction in water wastage, energy consumption, and carbon footprint. Moreover, the financial implications of adopting smart systems are favorable in the long term due to the operational savings, despite higher initial investments. This research underscores the importance of integrating advanced technologies for sustainable water resource management and sets a foundation for further advancements in smart water systems, ensuring more efficient, responsive, and eco-friendly solutions to global water challenges.

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Not required, N/A

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## Conflict of Interest

The authors have no conflicts of interest to declare.

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