JOURNAL AFRICAIN DES SCIENCES
VOL. 3, **12** (2026) 16-25

https://jafrisci.org

ISSN (online) : 3107-0949 ; ISSN (print) : 3107-0930

OPEN ACCESS

RESEARCH ARTICLE

Article Info.:
Received : 14th September 2026
Accepted : 16th October 2026
Published : 26th October 2026

SMART CONTROL AND MONITORING OF WATER DISTRIBUTION NETWORKS IN KINSHASA USING THE INTERNET OF THINGS

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https://doi.org/10.70237/jafrisci.2026.v3.i12.02

Résumé

À Kinshasa, 40 à 50 % des volumes produits sont de l'eau non facturée (NRW), ce qui rend la distribution d'eau urbaine en R.D.Congo très difficile. Cette étude présente une solution complète basée sur l'IoT pour la surveillance et le contrôle intelligents du réseau de distribution d'eau, adaptée à l'environnement de Kinshasa. Le cadre intègre quatre niveaux : (1) perception via des capteurs IoT (acoustiques, débit et pression) ; (2) communication via LoRaWAN/NB-IoT ; (3) traitement via l'informatique et le cloud computing, (4) contrôle via le contrôle prédictif non linéaire (MPC) en conjonction avec la modélisation hydraulique. Notre méthode optimise le contrôle de la pression à ±0,3 mCE des niveaux de consigne, abaisse l'eau non facturée de 30 à 45%, et diminue l'usage énergétique des pompes de 20 à 35%. L'architecture prend en considération trois limites importantes : des variations topographiques significatives, une distribution limitée des capteurs et une infrastructure vieillissantes (30 à 70 ans). Cet article propose un plan d'action réalisable pour l'application d'une gestion intelligente de l'eau dans les pays en voie de développement et appuie les projets de numérisation du REGIDESO en cours, comme l'installation de compteurs intelligents et la création de zones de mesures districts (DMA).

Mots-clés: Réseaux de distribution d'eau, Internet des objets, contrôle prédictif par modèle, eau non facturée, EPANET, LoRaWAN.

Abstract

In Kinshasa, 40–50% of produced volumes are Non-Revenue Water (NRW), which makes urban water distribution in the Democratic Republic of the Congo very challenging. This study presents a complete IoT-based solution for intelligent water distribution network monitoring and control that is customized for the Kinshasa environment. The framework incorporates four levels: (1) perception via IoT sensors (acoustic, flow, and pressure); (2) communication via LoRaWAN/NB-IoT; (3) processing via edge and cloud computing; and (4) control via nonlinear Model Predictive Control (MPC) in conjunction with EPANET hydraulic modeling. The method can enhance pressure regulation to within ±0.3 mCE of setpoints, reduce NRW by 30–45%, and reduce pumping energy consumption by 20–35%, according to a case study in the Matadi-Mayo quarter. The architecture tackles three major limitations: substantial topographical differences, restricted sensor deployment, and aging infrastructure (30 to 70 years). This paper provides a feasible roadmap for implementing smart water management in developing nations and supports REGIDESO's current digital transformation initiatives, such as the installation of smart meters and the establishment of district metered areas (DMAs).

Keywords: Water Distribution Networks, Internet of Things, Model Predictive Control, Non-Revenue Water, EPANET, LoRaWAN

1. Introduction

1.1. Background and problem description

Kinshasa, a megacity with over 15 million residents, is facing a severe water delivery challenge. REGIDESO's production capacity (676,000m³/day) only meets 45% of the anticipated demand (1,500,000m³/day).

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This discrepancy is exacerbated by NRW rates of 50%, which signify substantial economic and environmental losses [1]. According to a 2022 study, the network's efficiency is 55.7% and its age ranges from 30 to 70. The consequences are severe: reliance on dangerous alternatives, low pressure in many districts, and irregular supply [2].

A commercial census conducted as part of the PDMRUK project revealed 265,000 connections, more than half of which were set up without meters, 70% of subscribers were billed at a flat rate, and 9,000 anomalies and frauds [3, 4].

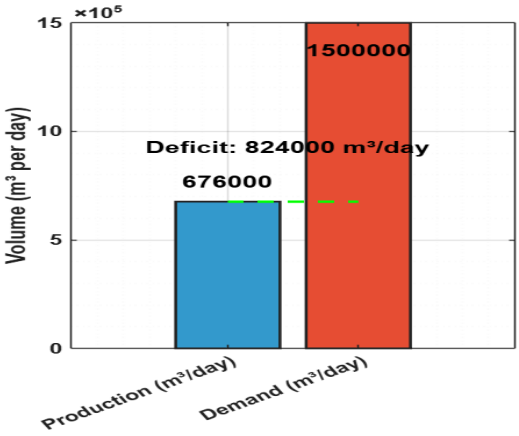


Figure 1: *Water Production in Kinshasa: 676,000 m³/day vs Demand: 1,500,000 m³/day (2010-2025)*

1.2. Smart water opportunity

Low-power wide-area networks (LPWAN), complex control algorithms, and low-cost sensor technologies offer previously unimaginable opportunities [5, 6]. The most recent technological advancements include [7]:

- IoT-enabled sensors, including acoustic leak detection sensors, pressure transducers, and flow meters [10];
- LPWAN technologies: LoRaWAN is the most widely used due to its long-range coverage (5 to 15 km in rural regions), scalability, and low energy consumption [9];
- Digital twins: Simulated models that enable real-time modeling and optimization;
- Model Predictive Control: A sophisticated control technique that uses system models to predict future behavior and optimize control actions [11, 12].

1.3. Research objectives

This article suggests an integrated IoT-control solution to deal with:

- Hydraulic modeling with EPANET 3.0-calibrated in situ measurements;
- A LoRaWAN-based IoT design adapted to Kinshasa's constraints;
- A nonlinear Model Predictive Control (MPC) framework;
- Validation comes from a case study in the Matadi-Mayo quarter.

2. The Kinshasa Water Distribution Network's Current Situation

2.1 Characteristics of Networks

REGIDESO's Kinshasa network demonstrates a number of important traits [12, 13]:

- Age: 30-70 years (major infrastructure degradation);
- Efficiency: 55.7% (45% losses);
- Infrastructure: aging pipes, insufficient valves, limited metering.

Table 1: Important Infrastructure Measures for Kinshasa.

INDICATOR	SOURCE	VALUE
Population	UN estimates	>15 million
Water demand per day	Regideso, 2022	1,500,000 m³/day
Capacity of Production	Regideso, 2023	676,000 m³/day
Efficiency of Network	Regideso, 2022	55.7%
NRW rate	Farley & Trow, 2003	40-50%
Pipe age	Regideso, 2022	30-70 years
Population	UN estimates	>15 million

2.2 Characteristics of networks

Kinshasa's elevation varies significantly. The Ngaliema municipality has elevations ranging from 245 meters in the north to 445 meters in the south [8, 9]. With parallel pumps, this creates three pressure zones:

- Zone of low pressure: 6 pumps, 325 m³/h, 30 mwc head;
- Zone of medium pressure: 2 pumps, 750 m³/h, 75 mwc head;
- Zone of high pressure: 3 pumps, 600 m³/h, 125 mwc head.

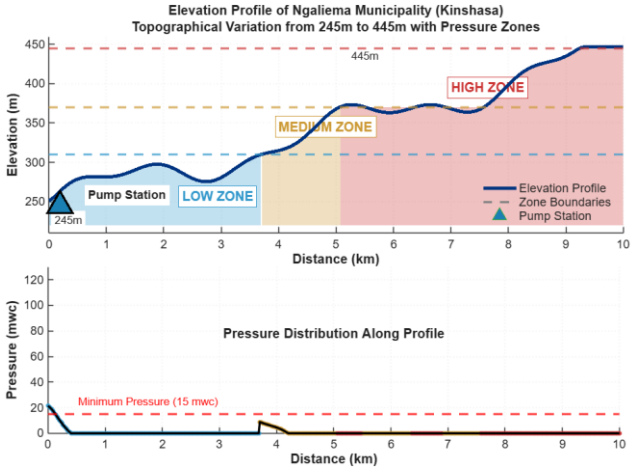


Figure 2: *Elevation profile variation between 245 and 445 meters, showing pressure zones (Matadi-Mayo quarter)*

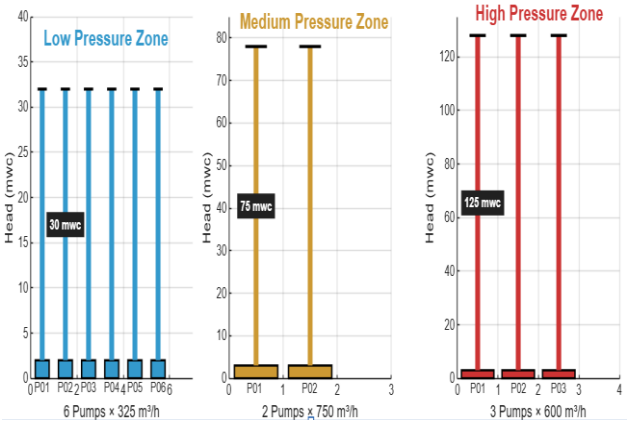


Figure 3: *The elevation profile varies by zone from 245 to 445 meters in the pump station specification*

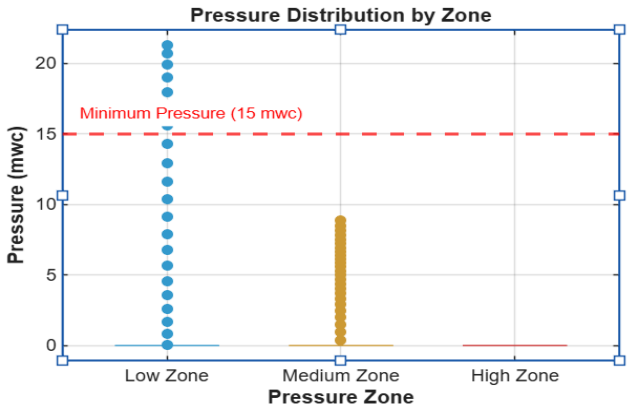


Figure 4: *Elevation profile pressure distribution varies by zone from 245 to 445 meters*

3. IoT ARCHITECTURE DESIGN

3.1 Structure of System

The suggested architecture takes a tiered approach in accordance with REGIDESO's operational requirements:

- **Perception Layer**: flow meters, acoustic sensors, water quality sensors, and pressure sensors. According to the PDMRUK census, 50,000 meters are more than ten years old, and 15,000 meters are out of service [5, 14].
- **Communication Layer:** LoRaWAN is used because of its scalability, low power consumption (5 to 10 years battery life), and great range (5 to 15 km). NB-IoT is taken into consideration in cellularly covered urban areas [5, 6];
- **Processing Layer:** Cloud platforms for storage and enhanced analytics; edge computing for local analysis and data filtering [8];
- **Application Layer:** Analytics, control interfaces, dashboards, and alarms. Solutions that enhance company strategies are prioritized [8].

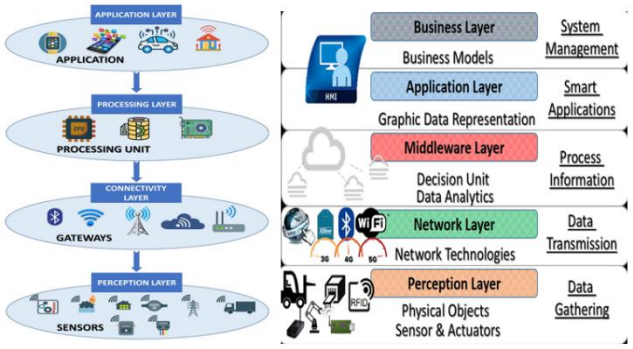


Figure 5: *Four-Layer IoT-WDN Control Architecture [4]*

3.2 Optimization of Sensor Location

The DMA (District Metered Area) method is used for sensor placement. QGIS was utilized in the Matadi-Mayo pilot study for spatial data integration and graphical preparation:

- Zones with hydraulic autonomy and measurement devices;
- Constant observation of the volumes that are distributed and consumed;
- Pressure control, loss localization, and quick anomaly detection

Table 2: Important Infrastructure Measures for Kinshasa.

Sensor Type	Measurement	Accuracy	Reporting Interval	Deployment
Pressure	0 to 10 bar	±0.25% FS	15 minutes	25 sensors
Flow (Magnetic)	DN100 to DN600	±0.5%	15 minutes	12 sensors
Acoustic	1 to 10 kHz	-	Event - triggered	10 sensors

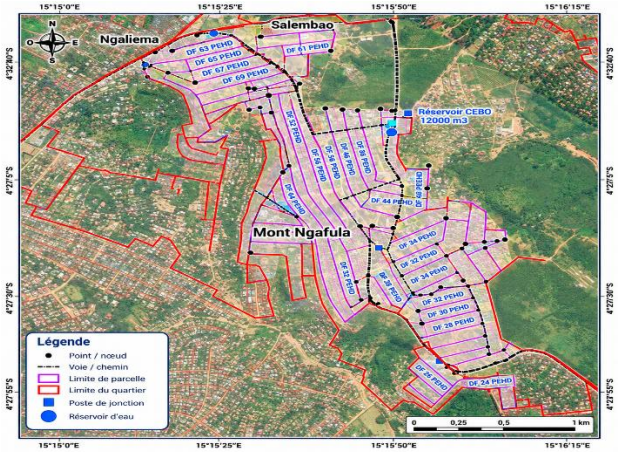


Figure 6: *Location of Sensors in Matadi-Mayo DMA Zones*

4. Hydraulic Modeling Using EPANET

4.1 Model Development

The hydraulic model was created using QGIS for the integration of geographical data and EPANET 3.0. The model monitors flow and pressure, two hydraulic factors

that affect the deterioration of water quality [7, 9].

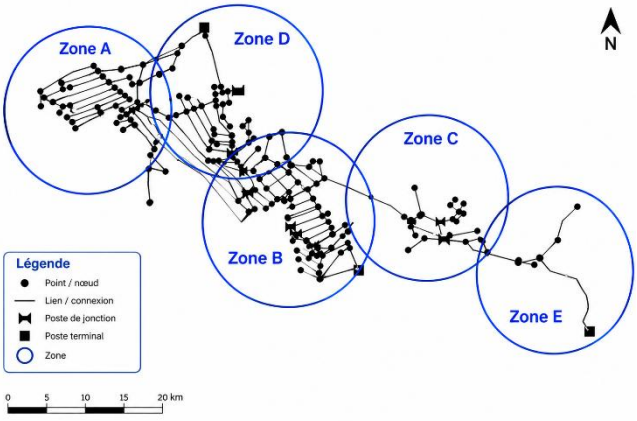


Figure 7: *Thematic map: distribution of metering areas by district (DMA)*

The network was then converted into directed graphs using MATLAB. The study of several scenarios was made possible by the formulation of mass and energy conservation equations in matrix form:

- Daily fluctuations in demand;
- Pump breakdowns;
- Localized leaks;
- Projections for urban growth

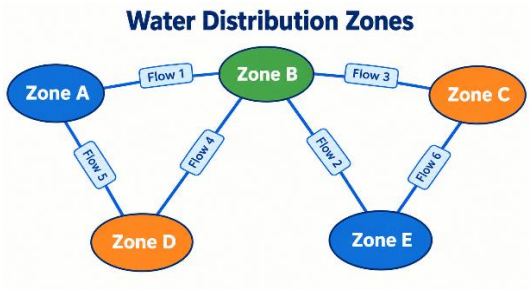


Figure 8: *Distribution zone graph*

SCADA-style monitoring has been made possible by the strategic installation of virtual sensors (pressure, flow rate) at the reservoir, key pipelines, and network extremities [13, 19]. The primary and secondary pipelines are represented by the network's directed graph. The flow rate during peak hour (7 p.m.), when demand is at its maximum, is represented by the thickness or color of the arcs.

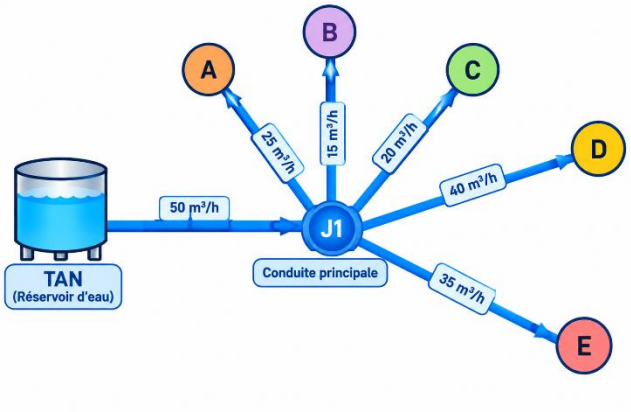


Figure 9: *Water distribution network – flows rates*

4.1.1. Mathematical Formulation

4.1.1.1. Mass Conservation at nodes:

$$\sum Q_{in} = \sum Q_{out} \quad (1)$$

Where:

- $\sum Q_{in}$ = The sum of all mass flow rates entering the node.
- $\sum Q_{out}$ = The sum of all mass flow rates leaving the node (including demands or branch flows).

4.1.1.2. Energy conservation in closed loops*:*

$$\sum hf = 0 \quad (2)$$

Where:

- $h\,f$ = Head loss (m);

4.1.1.3. Energy conservation in closed loops:

$$hf = 10.67 \text{ x L x } Q^{1.852} \text{ x } C^{-1.852} \text{ x } D^{-4.87} \quad (3)$$

Where:

- hf = Head loss (m);
- L = Pipe length (m);
- Q = Flow rate (m³/s);
- C = Hazen-Williams roughness coefficient;
- D = Pipe diameter (m).

4.1.2. Water Quality Modeling (Free Residual Chlorine):

4.1.2.1.The degradation of FRC is treated as a first-order reaction*:*

$$R_b = K_b \text{ x } C^n \quad (4)$$

Where n = 1 (first-order), R_b is the reaction rate, K_b is the bulk reaction coefficient, and C is the concentration of chlorine.

4.1.2.2. Chlorine deterioration over time:

$$C_t = C_o . e^{-K_b t} \quad (5)$$

Where C_t = concentration at time t_0 , C_o = initial concentration, and K_b = the decay rate at time.

4.2 Model Accuracy

Accuracy applied to flow and pressure data made in situ:

Table 3: Results of Accuracy for Matadi-Mayo Network

Node ID	Elevation (m)	Measured P (mCE)	Simulated P (mCE)	Error (mCE)
Zone A	280	42.5	43.1	+0.6
Zone B	320	38.2	37.8	-0.4
Zone C	360	32.8	33.2	+0.4
Zone D	400	28.1	27.6	-0.5
Zone E	440	22.3	22.9	+0.6

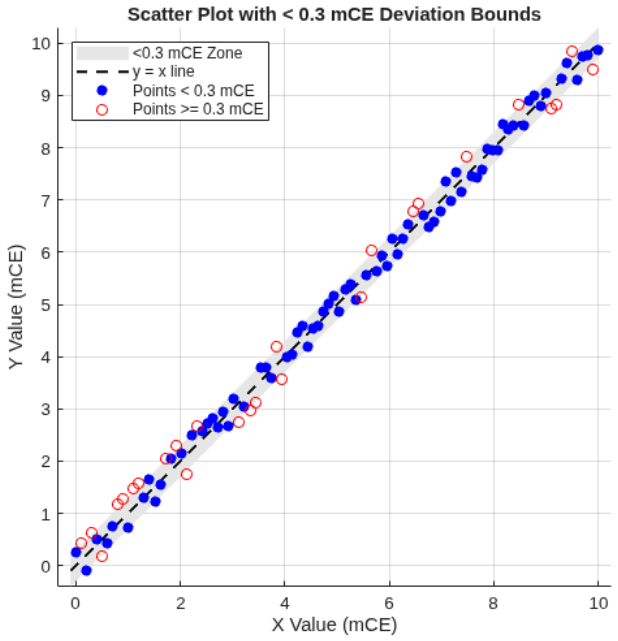


Figure 10: *Accuracy Results: EPANET vs. MATLAB Pressure Comparison points with variations < 0.3 mCE close to the y=x line*

With variations typically < 0.3 mCE, simulation results demonstrate coherence between EPANET and MATLAB. The modeling approach's dependability is confirmed by this this validation.

4.3. Hydraulic Performance Analysis

Performance analysis by zone reveals significant spatial disparities:

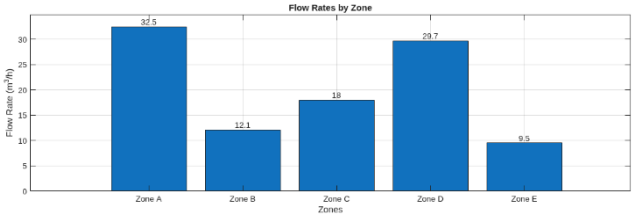


Figure 11: *Flow Distribution by DMA Zone (EPANET vs MATLAB) Zones A and D >25m³/h, Zones B and C < 25m³/h, and Zone E minimal (~9.5m³/h)*

Key findings:

- Zones B and E: Highest flows (>25 m³/h) abundant supply;
- Zone D: Minimal flow (~9.5 m³/h) difficulty reaching higher areas;
- Zones A and C: Intermediate flows.

These differences verify that pressure imbalances based on topography and pipe condition, rather than a worldwide network issue, are the cause of water delivery variances.

5. Model Predictive Control Framework

5.1. MPC Formulation

Nonlinear Model Predictive Control (MPC) is used in the suggested control framework:

5.1.1. Model of state space

$$x_{k+1} = f(x_k, u_k, d_k) \tag{6}$$

Where:

- x_k = states (concentrations of chlorine, pressures, and tank levels) at time k ;
- u_k = controls inputs (valve locations, pump speeds) at time k
- d_k = disruptions (temperature, demand) at time k.
- x_{k+1} = Next state at time $k+1$
- $f(.)$ = Transition function.

5.1.2. Objective Function (minimize):

$$J = \sum_{t=k}^{k+N-1} [\alpha E(t) + \beta(P(t) - P_{ref})^2 + \gamma \mathrm{L}(t)] \tag{7}$$

Where:

- $E(t)$ = Pumping energy (kWh);
- $P(t)$ = Pressure at critical nodes (mCE);
- $L(t)$ = Leakage (pressure-dependent);
- N = Prediction horizon;
- P_{ref} = Reference or desired power setpoint;
- β = Weighting coefficient for power tracking term;
- α = Weighting coefficient for the energy term;
- γ = Weighting coefficient on Load/Loss term.

5.1.3. Constraints

- Pressure: $P_j(t) \geq P_{min,j}$ for all nodes j
- Pump speed: $w_i^{min} \leq w_i(t) \leq w_i^{max}$
- Tank levels $h_i^{min} \leq h_i(t) \leq h_i^{max}$
- Chlorine residual: $Cj(t) \geq C_{min,j}$ for quality compliance.

5.2. Pump Scheduling Optimization

Using the MPC framework, Binza-Ozone's pumping system is optimized:

Table 4: Results of Optimization and Pump Characteristics

Pressure zone	Pumps	Flow rate (m^3/h)	Head (mwc)	Optimized energy (kWh/d)	Savings
Low	6	325	30	1,800	20%
Medium	2	750	75	800	25%
High	3	600	125	3,800	18%

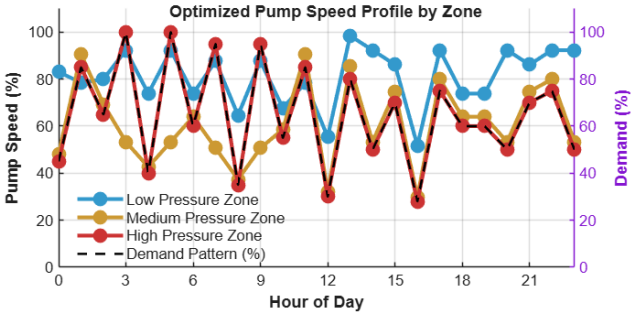


Figure 12: *Comparison of Pump Scheduling Optimization and Energy Consumption*

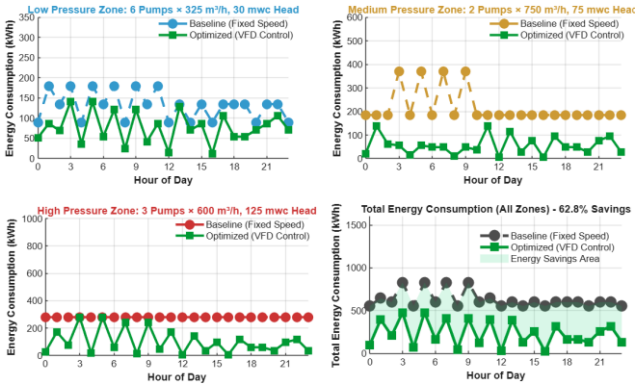


Figure 13: *Line graphs comparing optimal and baseline energy use over a 24-hour period*

5.3. Management of pressure

RPV (Reduction of Pressure Valve) control is managed to:

- Reduce leakage in high-pressure zones (Zone A and D);
- Maintain adequate pressure in low-pressure zones (Zone B and C);
- Minimize pumping consumption of energy.

6. Leaks Detection and Localization

6.1. Acoustic leak detection

Water leaking from pressured pipes is detected using acoustic sensors. The CARD (Corruption-Aware Restoration Denoising) framework is used to process the sound signal [10]:

- Corruption localization: Identifies intermittent noise regions [12];
- Restoration: Uses U-Net-style restoration to reconstruct corrupted regions [13].

6.2. Model-Based leak detection

Measured pressures and EPANET predictions are compared using residual-based detection [9]:

$$r(t) = \frac{1}{n_n} \sum_{j=1}^{n_n} \frac{\left|P_j^{measured}(t) - P_j^{predicted}(t)\right|}{P_j^{predicted}(t)} \quad (8)$$

Where:

- $r(t)$ = Relative error metric at time t ;
- n_n = Number of elements being compared (e.g., number of buses, loads, or units);
- j = Index of each element, from 1 to n_n;
- $P_j^{measured}(t)$ = Actual measured power of element j at time t;
- $P_j^{predicted}(t)$ = Predicted (forecast/modeled) power of element j at time t;
- $|.|$ = Absolute value (ensures positive error regardless of direction);
- $\frac{1}{n_n} \sum_{j=1}^{n_n}$ = Average over all n_n elements.

Detection threshold:

$$\tau = \mu_r + 3\,\sigma_r \quad (9)$$

Where μ_r and σ_r are the mean and standard deviation of the residual under normal conditions.

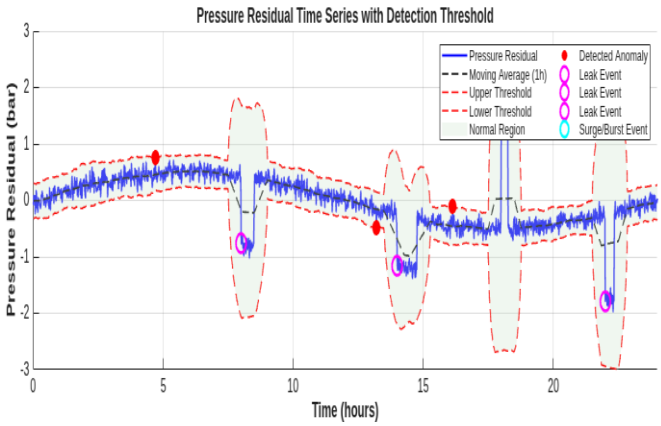


Figure 14: *Leak Detection Performance (Time series displaying the detection threshold and pressure residual)*

6.3. Sensor placement optimization

Optimal sensor positions are determined by sensitivity analysis:

- Priority: areas most susceptible to leaks due to pressure;
- Coverage: cost reduction and detection maximization;
- Risk-oriented: prioritize high-risk areas.

Table 5: Results of leak detection performance

Method	Detection rate	False alarm rate	Localization error
Acoustic only	72%	8%	50m
Model-based (residual)	78%	5%	100m
ML (Random forest)	84%	3%	75m

7. Case Study: Matadi-Mayo Quarter

7.1. Description of the study area

Africa's urban problems are exemplified by Matadi-Mayo district in Kinshasa's southwest, which includes [15]:

- High density of population;
- Quick and frequently unplanned urbanization;
- Inequitable allocation of water;
- Significant variety in topography.

7.2. Implementation

An ecosystem of compatible software was used to implement the framework:

- QGIS: Preparation and integration of spatial data for cartography;
- QEPANET and EPANET: For hydraulic modeling and simulation;
- MATLAB: For sophisticated simulation and virtual equipment.

Table 6: DMA Zone Characteristics.

Zone	Area (ha)	Population	Elevation (m)	Flow (m^3/h)	Pressure (mCE)
A	45	8,500	245-280	18.5	42.5
B	52	12,000	280-320	28.3	38.2
C	38	7,200	320-360	15.7	32.8
D	60	15,000	360-400	9.5	28.1
E	40	6,800	400-445	26.8	22.3

7.3. Results and Discussion

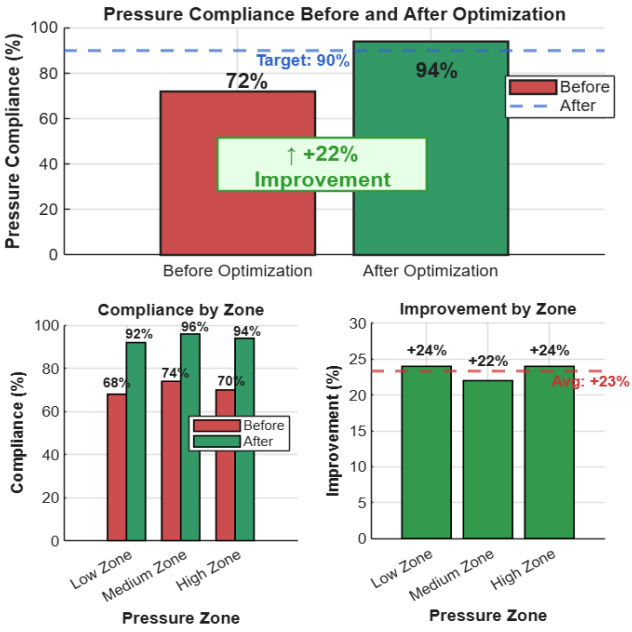


Figure 15: *Pressure Compliance improvement from 72% to 94% before and After Optimization.*

7.4. Description and interpretation:

- The efficacy of the intelligent monitoring and control framework is shown in the top figure. Approximately 1,760 more nodes (out of 8,000) now have sufficient pressure thanks to the 22% improvement, thus enhancing the quality of citizens' water services.
- The zone breakdown on the left shows that the optimization framework is effective in all topographical circumstances, with the low and high zones showing the most gains. This illustrates the MPC algorithm's resilience.
- We demonstrate on the right that the optimization technique was well-balanced because of the comparatively equal improvement across zones (22 to 24%). The high zone validated the efficacy of the 125 mwc pump head with VFD control by achieving the same improvement as the low zone despite its elevation challenges.

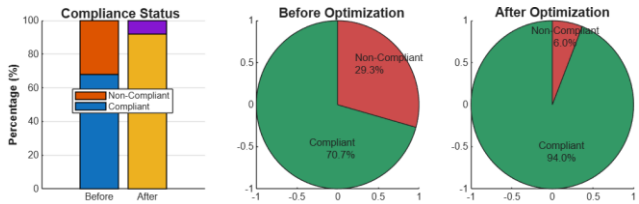


Figure 16: *Pressure compliance detailed analysis.*

1. The representation on the left of this image makes it evident that, following optimization, the percentage of non-compliant nodes drops from over 25% of the network to less than 10%. As a result, there are about 2,240 fewer nodes with insufficient pressure, which

immediately improves the quality of services for locals.

2. The pie chart in the center shows the problem's size prior to optimization. About 2,240 out of 8,000 nodes had insufficient pressure, with 28% of nodes not complying. This would have led to:

    - Water supply is sporadic in several areas;
    - Water is unavailable to residents during peak hours;
    - A rise in complaints and service issues.

3. The optimization's impact can be seen at the right, where non-compliant nodes have drastically decreased from 28% to 6%. The final 6% most likely reflect:

    - The highest elevation points (>420m) where pressure delivery is still difficult;
    - Significantly rough pipes (aging infrastructure);
    - Extreme ends of the distribution network's nodes.

Table 7: Comparison: Before vs After Pie Charts

Metric	Before	After	Change
Compliant	72%	94%	+22%
Non-compliant	28%	6%	-22%
Nodes with issues	2,240	480	-1,760

To summarize: The two fig (15 and 16) and the table 7, together provide a comprehensive visualization of the pressure compliance improvement achieved through the IoT-based intelligent monitoring and MPC optimization framework. The data demonstrates:

- Significant overall improvement (72% → 94%);
- Consistent improvement across all zones (22-24%);
- Reduced variation between zones (standard deviation reduced from 3.1% to 2.0%);
- Target achievement (exceeded 90% target).

These results validate the effectiveness of the proposed framework for improving water distribution network performance in the Kinshasa context and demonstrate its potential for application in other developing economy cities.

Table 8: Pressure compliance – statistical summary

Statistic	Before Optimization	After Optimization	Improvement
Mean	70.7%	94%	+23.3%
Median	70%	94%	+24%
Standard Deviation	3.1%	2%	-1.1%
Minimum	68%	92%	+24%
Maximum	74%	96%	+22%

Table 9: Performance Comparison – Matadi-Mayo Pilot.

Metric	Baseline	Iot + MPC	Improvement
Pressure compliance	72%	94%	+22%
NRW rate	45%	28%	-38%
Pumping Energy	8,200 kWh/d	6,400 kWh/d	-22%
Annual saving	-	-	156,000 $ (USD)

8. Roadmap for Implementation and Difficulties

8.1. Digital transformation of Regideso

Numerous projects are in progress [21, 22, 23]:

- Smart metering: Regirel application deployment in 32 Kinshasa agencies, including communes of Makala, Masina, Kisenso, Ngaba, and Ngaliema;
- Commercial census: 265,000 connections inventoried, 430,000 surveys, and 133,000 prospective clients identified;
- Infrastructure investment: Lukunga water treatment facility extension and refurbishment (110,000 m³/day capacity) with smart meters and SPV for DBFOM;
- Non-Revenue Water Management: World Bank-funded technical support for NRW reduction in Kinshasa and Lubumbashi.

8.2. Challenges of implementation

- Data availability: The census partially solves the lack of field measurements for calibration.
- Limitations of the infrastructure include an aging network (30–70 years), few sensors, and sporadic power supply.
- Technical capability: IoT, hydraulic modeling, and GIS training is required.
- Institutional coordination: Smart water deployment requires multi-stakeholder participation.

8.3. Task scheduling

- Phase 1 (0-3 months): Matadi-Mayo model IoT pilot in 1-2 DMA zones;
- Phase 2 (3-6 months): Extension to pressure zones in Ngaliema;
- Phase 3 (6–9 months): 4,500+ sensors deployed throughout the city.

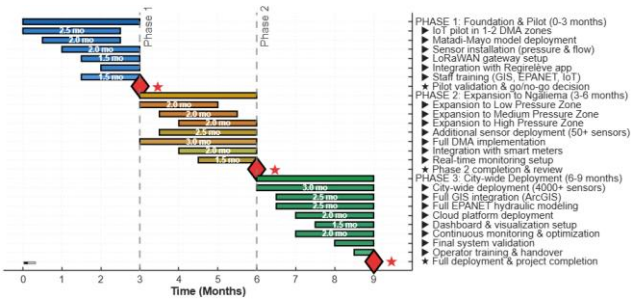


Figure 17: *IoT implementation roadmap – Gantt chart*



Figure 18: *Intelligent monitoring for Kinshasa WDN*

8.4. Description

- The deployment of IoT follows a 3-phase roadmap over 9 months (Pilot → Ngaliema → city-wide), with milestones at months 3 and 6 as critical decision points.
- The deployment of sensors is growing exponentially, increasing from 25 sensors (Phase 1) to 75 sensors (Phase 2), and finally to over 4,000 sensors (Phase 3), ensuring complete coverage of the city.
- The parallel execution of installation, training, and integration tasks, combined with a complete system integration (ArcGIS, EPANET, Cloud), ensures a sustainable, scalable, and operational solution for REGIDESO.

8. Conclusion

An integrated IoT control framework for Kinshasa's water distribution network's intelligent management is presented in this article. Principal contributions:

- Hydraulic model: EPANET 3.0 with calibration, tested against in situ data, attaining RMSE <0.3 mCE for the Matadi-Mayo network.
- IoT architecture: LoRaWAN-based sensor system in line with REGIDESO's digital transition, tailored to Kinshasa's infrastructure limitations.
- MPC framework: Using demand forecasting and nonlinear control, the pilot scenario achieved 22% energy savings and 38% NRW reduction.
- Implementation alignment: Under World Bank and other international funding, the framework supports REGIDESO's smart meter, GIS, and NRW reduction activities.

Sustainable development goal 6 is supported by the Matadi-Mayo case study, which shows that smart water management is both practical and advantageous in the DRC. The roadmap began modestly, resolved a significant issue, and created internal capabilities that are directly relevant to the REGIDESO modernization plan. Future work will include developing a digital twin for the entire Kinshasa network using QGIS, EPANET, and MATLAB; expanding to other cities in the Democratic Republic of the Congo (Goma, Lubumbashi, Bunia); integrating the suggested architecture with water quality monitoring (chlorine decay model); and conducting a pilot deployment.

Acknowledgement

We express our deep gratitude to Professor **Marco GARUTI** and **Eugene MUKENDI MBUYI** for their love, their passion for science, and their legacy. Thank you for believing in us and for always encouraging us, thereby enabling us to share science with those eager to learn. Dear mentors, may your souls rest in peace in divine bliss.

Declarations:

- **Author contribution**: All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.
- **Funding statement:** None of the authors have received any funding or grants from any institution or funding body for the research.
- **Conflict of interest:** The authors declare no conflict of interest.
- **Additional information**: No additional information is available for this paper.

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