Smart water distribution for smart cities based on Internet of Things

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ABSTRACT

Against an unprecedented water crisis in our country, balancing water supply and demand is necessary for a secure and sustainable water supply. This challenge requires systems capable of delivering the necessary quantities while conserving resources. Numerous research initiatives focus on addressing water distribution challenges with the help of smart water systems to optimize network operations and minimize water demand. Based on these advancements, this paper proposes a new smart water distribution system for southwest of Algeria. The system integrates the Internet of Things (IoT), information and communication technologies, and smart technologies to address critical attributes for enhancing efficiency. To achieve the efficient management of two-way flows (both water and data) based on water demand and its availability, two innovative architectures have been proposed, using various measurements of water quantity and quality parameters. Algorithms to automate and optimize water distribution are also proposed. According to obtained results, performance has improved, with an accuracy rate of over 98%. These results establish the suggested system as a strong option for intelligent and sustainable water resource management by demonstrating its efficacy and durability.

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1. INTRODUCTION

For life to exist on Earth, water is a necessary resource. However, there are worries of a water shortage due to the substantial rise in water usage brought on by the expanding human population, quick economic growth, and uneven urbanization [1]. In contrast, water scarcity is expected to be halved by 2025 in developing countries and by only 18% in industrialized countries due to population growth and industrial expansion [2]–[4].

In Algeria, existing water distribution systems are not automated, and face many problems, including obsolete infrastructure, vulnerability to natural disasters, water losses due to leaks, water pollution, and high-energy consumption. To address these challenges, many recent studies have proposed solutions to automate water distribution systems [4]–[6]. Thus, due to Algeria's abundant water resources, advanced wireless technologies, research expertise, and financial capacity, the country is well-positioned to adopt smart water systems (SWS).

In recent years, governments, businesses and analysts have seen growing interest in integrating smart technologies, including wireless sensor networks, information and communication technologies and Internet of Things (IoT) into water distribution systems. In this regard, these papers offer IoT, artificial intelligent (AI), and sensor-based smart water network management and monitoring solutions that maximize water resource use, quality, and sustainability [7]–[11]. However, most of these works focus on system architecture and monitoring functions. While water quality management and quantity control have been considered as separate issues. Authors in residential metering, water quality monitoring, leak detection, and energy management are the four solution areas that Cahn in [12] go into detail into after presenting a broad smart water network (SWN) framework. Although this framework provides comprehensive structure, it does not integrate optimization and intelligent control strategies for dynamic water distribution. In [13], a solution based on IoT and the use of advanced tools such as sensors, geographic information systems (GIS) and WaterGEMS is presented. Whose objective is the reduction of water losses by managing the pressure in distribution networks. However, this approach is still limited to hydraulic optimization and does not take into account water quality treatment and integrated control strategies. The Okoli and Abaso in [14] highlight the use of technologies in the construction of smart water systems based on IoT, 5G communication module. In addition, they explored the scenario of introducing 3D printing and solar energy to ensure the sustainability of the system. Additionally, Reza *et al.* [15] suggested a low-cost, low-power, long-range, and scalable method for monitoring water quality using a LoRa module based on the LoRaWAN protocol, a low-power wide area network (LPWAN) technology. However, these solutions are based on addressing detection and connectivity aspects, without integrating coordinated control management of water distribution. Sarraf *et al.* [16] presents a model of smart water meter with water quality monitoring. The suggested system uses a variety of sensors, a Raspberry Pi as the controller, and the cloud to store the data from the Raspberry Pi and transmit commands to it for measuring water quality and managing water distribution. Whereas this system demonstrates the feasibility of using IoT technologies, it does not provide a comprehensive framework of water distribution management at a network scale. Adeoti *et al.* [17] offer a suggested method for assessing how well smart water management technologies work to strengthen Nigeria's infrastructure's sustainability and resilience. Data is collected over a period of 1,095 days from a smart water kiosk. The results show a reliability rate of 97.1% and a sustainability of 100%. In contrast, the applicability of this study is limited in more complex or water-scarce environments because it focuses on performance metrics rather than intelligent decision-making or adaptive control mechanisms. Recent advances in the field of smart water are presented in this editorial [18], highlighting the integration of smart technologies such as AI, IoT and data analysis for sustainable management of water infrastructure. In this work [19], a smart solution for a citywide water distribution network is proposed for Indian scenario based on IoT. Smart water metering infrastructures that allow constant bidirectional data interchange on demand and between metering devices, water flow equipment, utilities, and end users were examined by Amaxilatis *et al.* [20]. Nevertheless, control and evaluation are treated as separate modules in most works.

With the advent of IoT, the quest for smart water management system is gaining attention. In this context, to address the limitations and research gaps identified in the above analysis, this paper in this paper proposed a new smart water distribution system for southwest Algeria (case study: Bechar City) based on IoT, information and communication technologies (ICT) and the use of smart technologies. This solution is designed for efficient management of bidirectional water flow and data based on water demand and availability. This new water distribution system will consist of water quality sensors (PH sensor) and water level measurement sensors, controllers (Raspberry Pi), actuators, pumps, solar panel systems, software (algorithms), and a computer network simulation. In addition, two architecture models are also proposed for the efficient management of water supply. As a result, this proposed system will enable real-time monitoring of water consumption, control of water quality and optimization of water distribution by the different houses of a city. Simulation results show that our proposed system has good performance and efficiency. Our proposed system offers a dynamic and adaptive model for managing water demand, in contrast to current systems that rely on static water consumption bases and it is suitable for water-scarce environments, such as the Saharan City of Bechar in southern Algeria, because it integrates water quantity and quality in real time.

This paper's remaining sections are organized as follows: The suggested general architecture of a smart water system in southern Algeria, the suggested hierarchical network, and a new design of a smart and water-saving distribution system within the framework of a smart city comprise the methodology part. Lastly, the simulation results and commentary are presented in the final section.

2. METHOD

A two-level design approach is presented in this section. A general smart water system design is described in the first level, which covers the key domains from water production to distribution and final consumption of water. The suggested data flow and software flowcharts are derived from our proposed smart city distribution system, which is the specific focus of the second level.

2.1. Proposed of general design of smart water system

We will explain the components of the proposed system as shown in Figure 1, detailing the tasks of the elements in achieving smart water management.

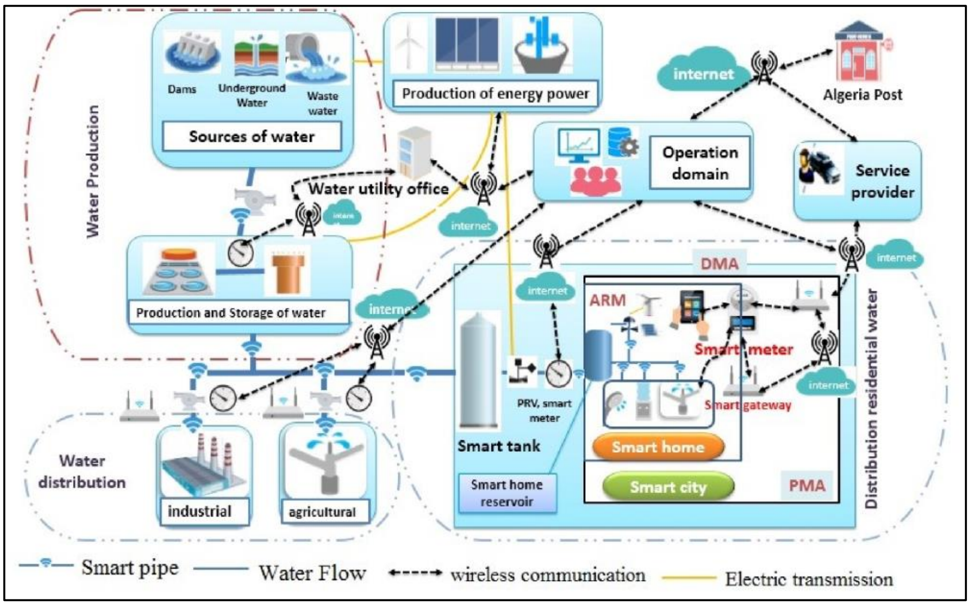

Figure 1. Proposed smart water grid in the south of Algeria

2.1.1. Water production

The field of water production consists of three essential phases: abstraction, treatment and storage. It is linked to the field of transport with intelligent connections (smart pipes) using smart sensors to detect flow and pressure. It also communicates via an internet interface with the operations service area and the water services office to balance water supply and demand.

2.1.2. Water distribution

The generated water is transmitted to the distribution area via several smart transmission lines. It takes responsibility for supplying drinking water to consumers according to user demands and the availability of water resources. This region's stability is tracked and managed to supply clean drinking water. Then, water is supplied to customers and utilities through service providers, it also provides smart services such as water use management and domestic water production. The operation and control center is responsible for hosting the control of the water system in the respective areas, *e.g.* distribution management systems (DMS), water management systems (WMS) in production and transport systems, micro-network management systems, SCADA systems. The Smart home customer domain includes homes, commercial or industrial buildings. It is connected with the smart water network via the smart meter and allows interaction between the customer and the utility. The home area network (HAN) interconnects all the smart devices in the home such as smart faucets, smart tanks and control devices to link them to the smart metering system. Finally, the micro-grid shown in Figure 1 is a water distribution system that includes several nano-grids and distributed storage tanks and a control system. It communicates with the other fields using wireless communication that transmits data information via smart meters. This solution aims to satisfy consumers in a reliable, secure and economical manner. The objectives of which are as follows:

- This two-way communication of both water and data allows consumers to have better control of their water consumption and provides more choice for the customer.
- Make the water distribution system robust against failures.
- Improve system reliability.
- The customer can in fact be a water supplier instead of a consumer (injecting the excess water into the network).

2.2. Proposed hierarchical network architecture

We have organized the network into several distinct layers to simplify the complex process of data flow management and ensure the adaptability and efficiency of the system. Figure 2 shows that the devices in our proposed system are deployed in a hierarchical network architecture (cluster-based network) to remotely monitor and control the distribution of drinking water.

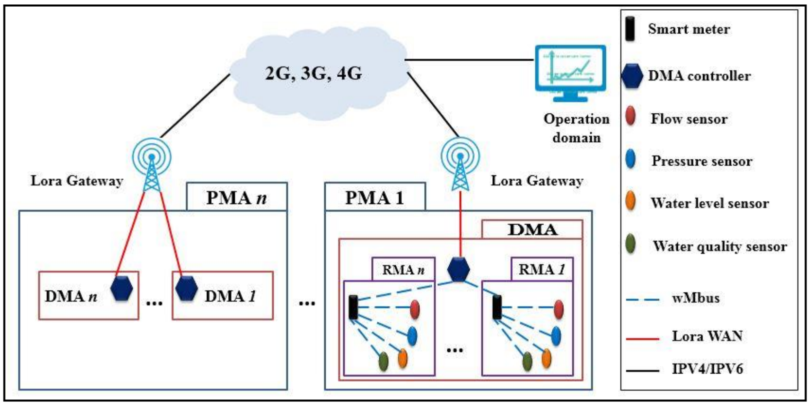

Figure 2. Proposed hierarchical network architecture

This approach offers several advantages such as minimizing energy consumption and optimal network management. Smart devices communicate with each other via the wM-Bus protocol, which is widely adopted by third-party water monitoring solutions in the residential metering area (RMA) area. The LoRa smart gateway is used to connect the RMA, district metering area (DMA) and pressure metering area (PMA) networks to the internet using several communication techniques (2G, 3G, 4G). Since, each RMA corresponds to an individual residential area (like a smart home), while DMA comprises several RMAs in the same city (smart city). While PMA contains several DMAs and thus allows for broader management of large-scale water distribution. In addition, additional communication protocols are also integrated, making the system adaptable to future developments. There are two interfaces on the gateways. While the second interface provides long-range low-rate communication based on LPWAN technology, the first interface communicates with connected smart devices using the wM-Bus protocol. In addition, our system is based on the application of data redundancy and aggregation mechanisms to ensure data reliability while optimizing energy efficiency.

2.3. A new proposed design for smart water-saving distribution system

The proposed system for a smart and water-saving network in a city is designed for efficient management of water consumption using advanced monitoring and control technologies. Our case study is situated on the left bank of the aqueduct Bechar, it is a rural town, which supplies the neighborhood market with farming items, and which is created around the old Ksar, the site is wealthy in water assets. The stock water comes to Ouakda spring (groundwater) at a stream pace of 8,000 m^3/d [21].

2.3.1. The system design

In this section, we suggest architecture for a smart water management system while keeping in mind the main analysis of the different approaches previously covered. The system shown in Figure 3 consists of wireless sensor network, renewable energy and electric power. It is composed of two parts: the source of drinking water (central and local reservoirs) and the water distribution network for end users. The WSN consists of several tiny devices (water level detection sensors (*e.g.*, HC-SR04 ultrasonic sensor), water quality sensors and controllers *e.g.* Raspberry Pi.). A distribution network is installed to distribute drinking water, so the solenoid valve controllers are installed in the pipelines. The solenoid valve controller, which is in charge of managing automatic water delivery, receives data from sensors that measure the pH of the water in the central and local tanks. The electric pump controller is responsible for activating or deactivating the electric pump based on the information coming from the sensors. The pump is charged either by renewable energies or by electric energy. The customer can also inject water into the network. As result, the installation of our system is simple and flexible, and in areas where water is scarce, this system can be used to avoid wasting water resources.

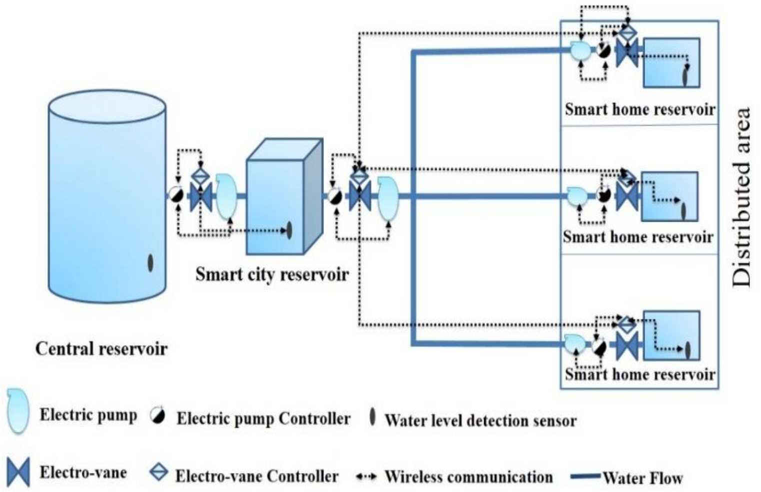

Figure 3. Proposed smart water distribution system design

Figure 4 illustrates the software system design. The wireless sensor node programs in our system are designed to continuously monitor water pH levels and water levels. These nodes transmit the collected data via a wM-Bus network to a LoRa smart gateway, which forwards it using internet-based communication technologies such as 2G, 3G, or 4G to a web service. The web service employs intelligent software applications to analyze the data and trigger actions accordingly, such as selectively activating controllers. Controllers determine whether to initiate filling of the smart tanks based on predefined threshold values for water level and pH in both the smart home tank and the smart city reservoir.

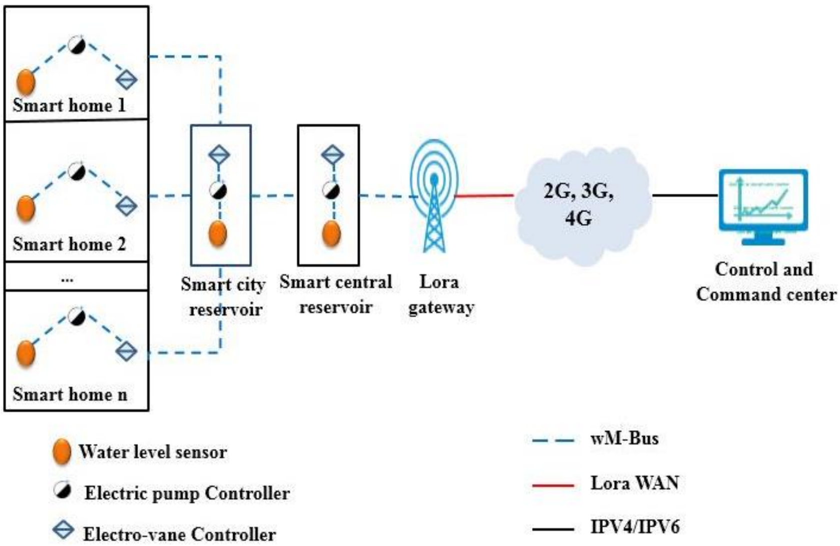

Figure 4. Proposed software system design

Flow charts of software design for sensors nodes, controllers and the Lora smart gateway are expressed in Figure 5. In the flowcharts for the water level sensor and the PH sensor, the first step is to set the time (T) of the low-power sleep mode for the sensor in order to minimize its power consumption. Then, the sensors reactivate after this period to collect water level data and PH of water respectively, in order to transmit them to a smart gateway for further analysis. Once the transmission is complete, the sensors go into sleep mode until the next cycle. This procedure is repeated continuously.

The controller node's flowchart, which likewise begins with a sleep mode state for a duration (T). Following this sleep phase, the controller enters active mode in order to accept the data sent by the sensors over the LoRa smart gateway. Following the completion of receipt, the controller evaluates the readings in respect to pre-established PH and water level thresholds. Based on the assessments already completed, the controller determines whether to turn on or off the solenoid valve in order to control the water distribution if needed.

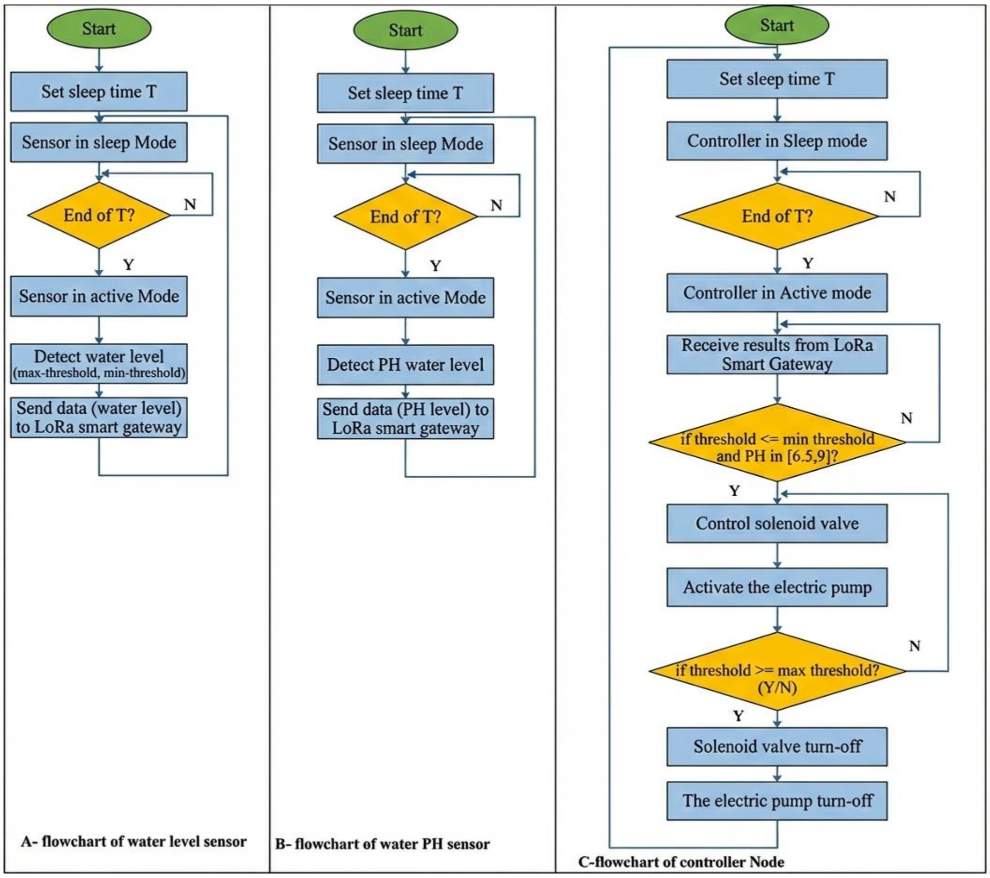

Figure 5. Flowcharts of water level sensor, water PH sensor and controller node

3. SIMULATION AND DISCUSSION OF RESULTS

To effectively validate our proposed approach, logic-based, data-driven simulation using real household water consumption records is used. The simulation environment consists of the experimental part, of which we have deployed the set of sensors (HC-SR04 ultrasonic sensor, Gravity Analog pH Sensor V2), the controllers (Raspberry Pi), and the solenoid valve as shown in Figure 3. The data obtained from the platform are then processed by the different algorithms mentioned in Figure 5. The implementation of these algorithms was coded in the Python language. Table 1 summarizes the key parameters used for simulation.

The lack of accurate data on water consumption complicates demand forecasts in Algeria. Estimates are often based on a typical consumption of 150 liters per person per day, without clear justification [22]. To fill this gap, we used wireless sensors network (WSN) to determine real water consumption data as a robust empirical database.

Table 1. Simulation parameters

Parameter	Value/description
Data collection period	Eight months
Number of households	Ten households
Sensors used	pH sensor: Gravity Analog pH Sensor V2 Water level sensor: Ultrasonic Sensor HC-SR04
Controller used	Raspberry Pi 3 Model B+
Sampling frequency	One measurement every hour (24 readings/day for each house).
Simulation duration	≈ Eight months
Programming language	Python 3.9

The results in Table 2 show that water consumption varies from one house to another, especially in March and April 2024, under the influence of several factors. This study demonstrates the effectiveness of a WSN to accurately monitor changes in water consumption and detect cases of misuse or leaks, ensuring intelligent and sustainable management of this resource. In order to understand individual water usage habits within households, we divided the total water consumption for each house by the number of members. The findings are presented in Table 3.

Table 2. Household water consumption in liters per day using WSN

House	Households water consumption Liters/Day							
	09/2023	10/2023	11/2023	12/2023	01/2024	02/2024	03/2024	04/2024
H001	440	345	215	260	295	280	430	470
H002	712	752	784	720	616	712	984	960
H003	348	288	180	280	316	352	360	472
H004	518	385	224	483	483	504	630	770
H005	260	220	180	200	192	208	240	296
H006	450	370	220	250	310	340	340	380
H007	136	180	160	196	172	168	236	232
H008	1320	1080	1200	900	1116	1128	1584	1800
H009	396	402	480	522	402	324	480	582
H010	232	140	168	200	204	296	280	368

Table 3. Per capita consumption (L/D)

House	Per capita consumption litres /day							
	09/2022	10/2022	11/2022	12/2022	01/2023	02/2023	03/2023	04/2020
H001	88	69	43	52	59	56	86	94
H002	89	94	98	90	77	89	123	120
H003	87	72	45	70	79	88	90	118
H004	74	55	32	69	69	72	90	110
H005	65	55	45	50	48	52	60	74
H006	90	74	44	50	62	68	68	76
H007	34	45	40	49	43	42	59	58
H008	110	90	100	75	93	94	132	150
H009	66	67	80	87	67	54	80	97
H010	58	35	42	50	51	74	70	92

In conclusion, precise information on the water usage patterns of each individual is provided by the calculation of water consumption per capita. These results help to clarify the strategies to be followed for improving the efficiency of sustainable water management.

3.1. Daily water consumption

Our proposed solution consists in detecting the exact daily water consumption for each household, monthly by using the WSN. Subsequently, we calculated adopted consumption values monthly for each household. Unlike the old system, where water consumption is done randomly which leads to significant waste, this solution allows to distribute water with necessary quantities according to the need and to the season, which proves the efficiency of our system in terms of water saving. As a result, our strategy perfectly conforms to the idea of smart cities for this resource's sustainable development. From the analysis of the results shown in Figure 6, we observe a recurring trend with two notable consumption peaks occurring at approximately the same time each month. A very low water consumption in the early hours of the night and an increase in consumption is noted from 6 am reaching a maximum at 10 am to 12 am, due to morning routines. After this notable peak, water consumption begins to decrease but remains fluctuating. Water consumption remains relatively stable between the different months, with an increase in periods of high demand. This graph demonstrates the effectiveness of our system in terms of detection and monitoring capacity with precision. In addition, our system is robust and allows long-term data collection for decision-making in optimal water management.

The analysis of the graph of the results presented in Figure 7 concerning the water consumption for house H002 in September 2023 shows remarkable variations in the daily consumption of water. However, a peak in consumption is illustrated at 12:00 with 120 liters and periods of low consumption especially during the night and evening are also recorded. Our system that uses WSNs allows accurately capturing consumption variations and identifying peaks and troughs in consumption, which demonstrates its reliability to monitor and manage water consumption effectively.

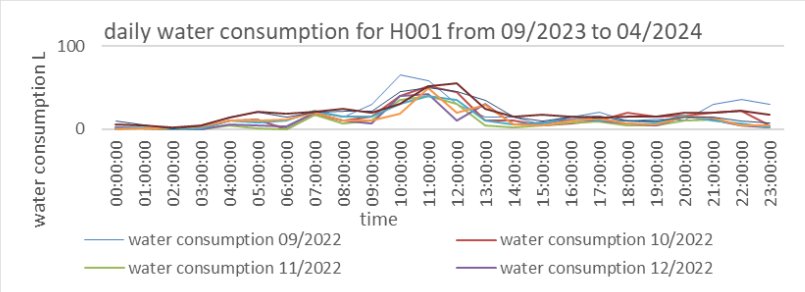

Figure 6. Daily water consumption for H001 from 09/2023 to 04/2024

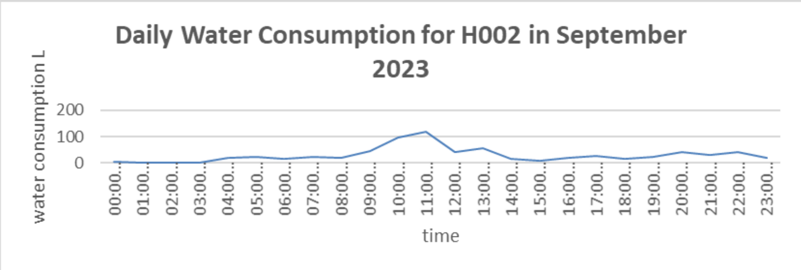

Figure 7. Daily water consumption for H002 in September 2023

3.2. Comparison between months

According to Figure 8, the analysis of the monthly water consumption for H001 results highlights several important points of the consistency, precision and reliability of the system. From the analysis of the results in Figure 8, we notice that there are significant variations in consumption between months with a minimum of 215 L/D in November and a maximum of 470 L/d in April 2024. The ability to detect these variations proves that our system is reliable and measures the data accurately.

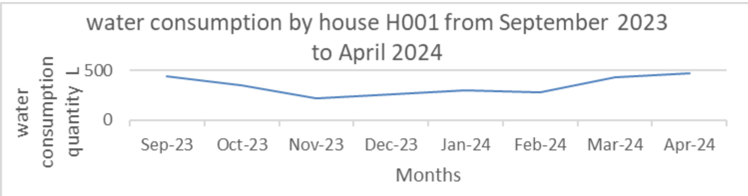

Figure 8. Monthly water consumption for household from 09/2023 to 04/2024

3.3. Optimization of our proposed smart water distribution management system

The optimization of smart water distribution management requires the determination of an approved consumption value in order to adopt it as a reference value to improve and optimize the allocation of water resources.

3.3.1. Choosing an approved water consumption value

To find the approved value of water consumption, we proposed to use a solution that consists of using a weighted average with dynamic analyses and safety margins, by applying the formula (1).

$$Approved\ value = Weighted\ average\ + Safety\ margins \tag{1}$$

We have inspired this strategy from other field of energy management [23] in order to apply it in our proposed system for the management of intelligent water distribution, whose future needs are estimated using averages of historical data and adding a safety margin to regulate variations. To calculate the monthly-approved values, we have followed the following steps:

a. Assign weights based on specific factors (*e.g.* number of occupants per house).
b. Do weighted average calculations for each month.

$$Weighted\ average = \frac{\sum_{i=1}^{n}(Consumption*Weight)}{\sum_{i=1}^{n} Weight} \quad (2)$$

In our study, we used a safety margin of 10% of the average consumption after several simulations. This choice is optimal for this system to efficiently manage unexpected variations in consumption. A safety margin was introduced to prevent both water shortage and over-allocation.

In addition, after several simulations, we chose the normalized weight range [0.5, 1.5] to optimize the weighted average in our proposed system in order to reduce the deviations between the target volume and the measured volume while improving the efficiency of the system. This decision is based on established research, such as in [24], [25]. The weight values presented in Table 4 are determined after several simulations and comparative analyses. These values ensure the optimization of resource allocation and the efficiency of the proposed system. Thanks to this approach, based on several simulations, we were able to identify the standard best suited to our specific context, guaranteeing intelligent and sustainable water distribution management.

Using these normalized weights and by applying formula (2), the weighted average value for the month of September is: 73.41 L/D. So, the safety Margin (10%)=7.341 L/D. Following the same steps, the approved monthly water consumption values were calculated by applying a weighted average based on the standardized weights presented in Table 3, to which a 10% safety margin was added to ensure robustness and flexibility to changes for our proposed system. The calculation results are presented in Table 5. Table 6 presents the optimized water consumption target values for all monitored houses, which are calculated based on the approved values presented in Table 5. These target values were determined by multiplying the approved value by the number of inhabitants in each household.

Table 4. Normalized weights for households based on number of inhabitants

Household	Number of occupants	Normalized weight
H001	5	0.625
H002	8	1.0
H003	4	0.5
H004	7	0.875
H005	4	0.5
H006	5	0.625
H007	4	0.5
H008	12	1.5
H009	6	0.75
H010	4	0.5

Table 5. Monthly approved values for daily consumption of inhabitant

Month	Approved daily consumption values/inhabitant
September 2023	80.75 L/D
October 2023	73.00 L/D
November 2023	72.10 L/D
December 2023	70.65 L/D
January 2024	72.91 L/D
February 2024	76.02 L/D
March 2024	93.85 L/D
April 2024	113.49 L/D

Table 6. Target values optimized for each house liters/day

House	Target values optimized for each house L/D							
	09/2022	10/2022	11/2022	12/2022	01/2023	02/2023	03/2023	04/2023
H001	403,75	365	360,5	353,25	364,55	380,1	469,2	567,45
H002	646	584	576,8	565,2	583,28	608,16	750,72	907,92
H003	323	292	288,4	282,6	291,64	304,08	375,36	453,96
H004	565,25	511	504,7	494,55	510,37	532,14	656,88	794,43
H005	323	292	288,4	282,6	291,64	304,08	375,36	453,96
H006	403,75	365	360,5	353,25	364,55	380,1	469,2	567,45
H007	323	292	288,4	282,6	291,64	304,08	375,36	453,96
H008	969	876	865,2	847,8	874,92	912,24	1126,08	1361,88
H009	484,5	438	432,6	423,9	437,46	456,12	563,04	680,94
H010	323	292	288,4	282,6	291,64	304,08	375,36	453,96

3.4. Comparison between our optimized smart water distribution system and the standard system based on 150 L/D/person

In this section, a comparison for the month of September between our proposed smart water system based on a distribution of the optimized values presented in Table 6 and a standard system based on a distribution of 150 L/D/person is presented. Table 7 illustrates this comparison.

The results presented in Table 7 show that, thanks to the use of smart technologies, our proposed system reduces the total volume to be distributed to 7,999.25 l/d, or 45.6% compared to the standard system. The proposed smart water distribution system not only saves water but also compensates for fluctuations in consumption by adding a 10% safety margin. It also minimizes pressure on water resources by distributing only the amount necessary to meet user needs and saves electricity, thus ensuring sustainable management. On the contrary, the standard system characterized by the generation of surpluses and waste of water.

Table 7. A comparison for the month of September between our proposed smart water system

Houses	Number of inhabitants	Optimized target volume (our proposed system) L/D for September	Standard target volume (traditional system) (L/D)
H001	5	403.75	750
H002	8	646.0	1200
H003	4	323.0	600
H004	7	565.25	1050
H005	4	323.0	600
H006	5	403.75	750
H007	4	323.0	600
H008	12	969.0	1800
H009	6	484.5	900
H010	4	323.0	600
	total	7999.25	14700

3.5. Volumetric accuracy rate of our system

The volumetric accuracy rate (VAR) is used to evaluate how accurately the proposed system delivers water quantities with respect to the target consumption demand. It represents the ratio between the effectively delivered water volume and the expected target volume. The formula (3) allows us to calculate the volumetric accuracy rate of our system:

$$VAR = 1 - \frac{|Vtarget - Vmeasured\,|}{Vtarget} * 100 \tag{3}$$

Calculate target volumes $Vtarget$:

$$Vtarget = approved\ value\,\frac{L}{D} * number\ of\ inhabitants\ for\ each\ house \tag{4}$$

As we have already calculated above that, the approved value is 80.75 L/d, in September. So, the calculations for each house are presented in Table 8.

Table 8. Measured and target volume values

Houses	Number of inhabitants	Target volume $Vtarget$ L/D	Measured volume $Vmeasured$ L/D
H001	5	403.75	440
H002	8	646.0	712
H003	4	323.0	348
H004	7	565.25	518
H005	4	323.0	260
H006	5	403.75	450
H007	4	323.0	136
H008	12	969.0	1320
H009	6	484.5	396
H010	4	323.0	232

Calculation of the differences for each house:

$$\Delta V = |\ Vtarget - Vmeasured\ | \tag{5}$$

Calculate the total volumes:

$$Vtarget, total = Vtarget$$
$$Vmeasured, total = Vmeasured$$

Digital application:

$Vtarget, total = 8070\ L/D$, $Vmeasured, total = 7978\ L/D$, $\Delta V\ total = 92\ L/D$, then $VAR\ \approx\ 98.86\%$.

This result (98.86%) of the volumetric precision rate of our system indicates that our system is efficient and the differences between the target and measured volumes are low, which makes it reliable in meeting water needs.

3.6. Water quality monitoring

In this work, we also suggested utilizing WSNs to create a continuous monitoring system for reservoir pH quality. This proposed system allows the collected data to be sent to the treatment center, an alert to be sent to the system in the event of anomalies or a system failure or if the PH values go outside the range predefined. The results in Figure 9 show that the PH level was generally stable in all houses (between 6.8 and 7.5). However, the system detected two anomalies (a PH peak at 09 and a drop at 06). These anomalies were alerted to the system for rapid treatment. This real-time detection and reaction capacity illustrates the robustness of our proposed system.

Figure 10 presents the workflow of a data-driven simulation model for our proposed smart water distribution system. First, water consumption and quality data are pre-processed using Python techniques, including cleaning and formatting, to ensure quality. In order to regulate water distribution, a control strategy is implemented using decision rules. Finally, the system generates an optimized water distribution.

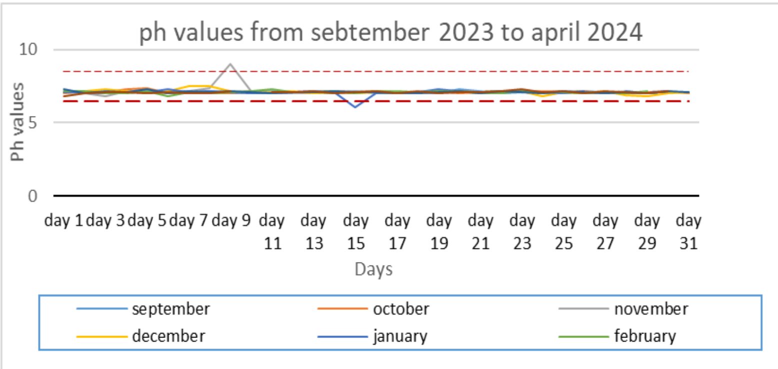

Figure 9. PH values from 09/2023 to 04/2024

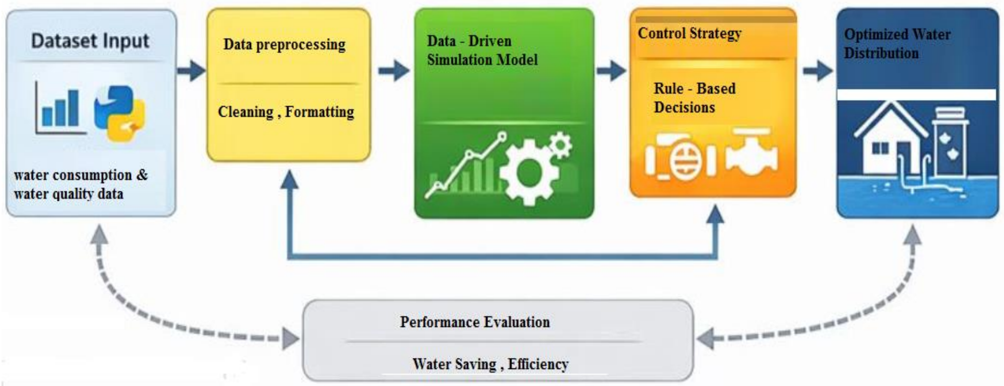

Figure 10. The workflow of a data-driven simulation model for our proposed smart water distribution system

4. CONCLUSION

Our contribution to the best possible water distribution management in a smart city is presented in this paper. The IoT intelligent technology serves as the foundation for this system. The main goal is smart and optimal management of the quantity and quality of distributed water. The architectures proposed for water distribution are characterized by easy deployment, modular flexibility, and reliability. The proposed system allows continuous monitoring of the distribution and quality of drinking water, as well as the ability to generate alerts in the event of detected anomalies. It also allows optimizing the quantity of distributed water by accurately determining the daily consumption for each home, unlike standard methods often based on the value of 150 liters/day/person. Therefore, our proposed system allows for water savings of 45.6% compared to the traditional model. In addition, the remarkable volumetric accuracy rate of 98.86% demonstrates that our system ensures consistent and adaptable management to actual needs, while reducing waste and ensuring resilience to consumption fluctuations.

Among the most important aspects of the proposed solution is the estimation of monthly approved values (*e.g.*, 80.75 L/D in September) for water consumption by applying mathematical optimization models inspired by the energy domain and based on actual consumption data collected via wireless sensor networks deployed to monitor the water distribution system. This determined approved value allows us to calculate adjusted consumption that fluctuates according to actual needs and seasons.

In order to increase the monitoring system's decision-making accuracy, we will incorporate low power sensor nodes, cutting-edge IoT communication technologies including Narrowband IoT (NB-IoT), artificial intelligence methods, and prediction approaches in our future work. We will also propose surplus water management, adjusting the quantity of water to be distributed based on actual daily consumption. This contribution will provide a foundation for researchers interested in working in this field and a prototype for manufacturers seeking to automate water distribution in modern, smart cities.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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