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Article

Internet of Things (IoT)-Based Wastewater Management in Smart Cities

Abdullah I. A. Alzahrani [1], Sajjad Hussain Chauhdary [2,*] and Abdulrahman A. Alshdadi [3]

1 Department of Computer Science, Collage of Science and Humanities in Al Quwaiiyah, Shaqra University, Shaqra 11961, Saudi Arabia; a.alzahrani@su.edu.sa
2 Department of Computer Science & Artificial Intelligence, College of Computer Science and Engineering, University of Jeddah, Jeddah 23890, Saudi Arabia
3 Department of Information and System Technology, College of Computer Science and Engineering, University of Jeddah, Jeddah 23890, Saudi Arabia; alshdadi@uj.edu.sa
* Correspondence: shussain1@uj.edu.sa

Abstract: Wastewater management is a mechanism that is used to extract and refine pollutants from wastewater or drainage that can be recycled to the water supply with minimal environmental effects. New methods and techniques are required to ensure safe and smart wastewater management systems in smart cities because of the present deteriorating environmental state. Wireless sensor networks and the Internet of Things (IoT) represent promising wastewater treatment technologies. The elaborated literature survey formulates a conceptual framework with an Internet of Things (IoT)-based wastewater management system in smart cities (IoT-WMS) using blockchain technology. Blockchain technology is now being used to store information to develop an incentive model for encouraging the reuse of wastewater. Concerning the quality and quantity of recycled wastewater, tokens are issued to households/industries in smart cities. Nevertheless, this often encourages tampering with the information from which these tokens are awarded to include certain rewards. Anomaly detector algorithms are used to identify the possible IoT sensor data which has been tampered with by intruders. The model employs IoT sensors together with quality metrics to measure the amount of wastewater produced and reused. The simulation analysis shows that the proposed method achieves a high wastewater recycling rate of 96.3%, an efficiency ratio of 88.7%, a low moisture content ratio of 32.4%, an increased wastewater reuse of 90.8%, and a prediction ratio of 92.5%.

Keywords: Internet of Things; wireless sensor networks; smart city; wastewater management

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1. Introduction

Water must be safe enough to be used for drinking, washing, and industrial use. Wastewater is any water that needs cleaning after use. The purpose of wastewater management is to preserve wastewater [1]. Untreated wastewater chemicals and pathogens can harm animals, plants, and birds that live in or near the water. Healthy wastewater management helps to reuse the water volume instead of waste it [2]. Thus, it contaminates crops and drinking water which impacts human health. Wastewater is a water supply with many uses, when correctly processed [3]. Treatment of wastewater is essential to protect many different habitats [4]. The beneficial use of wastewater often decreases the impacts of wastewater or industrial effluent contamination on the environment. The end usage of wastewater defines the appropriate water quality and safety control procedures [5].

Increased urbanization poses a danger of water shortages. Safe drinking water is one of the basic human needs. This refers to the notion of wastewater reuse and recycling [6]. The recycled wastewater is contained in an underground sump, and it is used for planting water. Using recycled water eliminates the dependence on ever costlier and cheaper groundwater for such applications [7] and will minimize the overflow and reduce wastewater discharge into rivers and oceans. Similar treatment standards occur for specific applications of water [8]. Treated and recycled wastewater offers an inexpensive supply that eliminates the demand and burden on freshwater supplies such as groundwater, rivers, and reservoirs [9]. In the areas impacted by water shortages and drought, this is especially relevant. Wastewater that is not extracted and recycled is often discharged into the wide water bodies [10]. The recycling of wastewater is the best way to prevent potential water depletion and minimize contamination that harms the ecosystem. Untreated wastewater does not automatically decompose [11].

Wastewater treatment is used to extract pollutants from waste or sewage and transform them into wastewater that can be reused for other uses (called water recovery) or added to the water supply with an associated environmental impact [12]. In a basic central device setup, a wireless sensor network is required, with the base terminal operating as the central hub [13]. The data are obtained, preserved, and analyzed afterwards. The hardware comprises a pump, a fluidic chamber, and various sensor nodes for tracking the fluid's color changes [14]. The change of color is tracked independently in the channel cabinet and the bulk solution. To track atmospheric conditions such as light levels and temperature, sensor nodes are often used [15]. An experiment showed the usefulness of wireless sensing in controlling water purification treatments.

Through detecting and avoiding mixed sewage and chemical overflows in wastewater using IoT sensors, intelligent wastewater systems can satisfy the demand for freshwater within the smart community of the IoT. Freshwater is one of the most valuable natural commodities that is not available every day. The IoT uses the concept of sensing devices installed at different points in the water environment for aquatic care [16]. These sensors capture and transmit data to surveillance systems. These data may include the water quality, temperature changes, pressure changes, water leakage detection, and chemical leakage detection. These sensors capture and transmit data to surveillance systems. A smart water sensor powered by the IoT can monitor the water quality, pressure, and temperature. In reality, a sensor solution can control the fluid flow throughout the treatment plant and can be used by a water utility provider. Using blockchain technologies to monitor these connections can efficiently analyze quantity communications, identify breaches in water mass balance management, and improve leak detection. If registered data can be changed retroactively in any particular block without modifying all additional blocks that need to be agreed by most networks, transaction process transparency and reliable and effective data management can be instantly enabled. Without the use of blockchain, the system will require a centralized repository and will be vulnerable to security threats. Moreover, it is difficult to incentivize the recycling and reuse of wastewater in industries and households without the concept of tokens/credits in the form of a cryptocurrency. The wastewater treatment anomaly detection algorithm is used to diagnose irregular actions (anomalies) and water activities not seen regularly. These can result from attacks on control components, a network, or the physical surroundings; failures; misconfigurations; or even standard bugs in the IoT sensors. Therefore, the ability to detect anomalies acts as a protective tool and helps to build and sustain.

The significant contributions of this paper include:

1. Designing an IoT-WMS for wastewater re-treatment and management to fulfil the water needs in a smart city.
2. Suggesting a blockchain technology for the reuse of wastewater in smart cities.
3. The anticipated cost-effectiveness and reliability of outputs compared to the current model undoubtedly eliminates conventional worldwide wastewater management.

The rest of the paper is structured as follows: Section 1 introduces the concept of wastewater management in a smart city. Section 2 presents a discussion on related work. Section 3 explores the IoT-WMS framework to improve wastewater management and encourage recycling wastewater in smart cities. Section 4 elaborates on the results and discussion based on an analysis in Section 3. Section 5 concludes the research with some future perspectives.

2. Related Work

In this section, we present some recent related works and establish their relevance to our proposed approach. A summary of related work is also presented in Table 1.

Table 1. Summary of related work.

Related Work	Problem Addressed	Technique Employed
Vibhas Sukhwani et al. (2020) [17]	Fresh and eastewater resource management in the rural–urban divide	Knowledge-based conceptual framework
H. K. Pandey et al. (2020) [18]	Determining physio-chemical parameters from samples of groundwater	Monitoring the water quality index using a geographical information system
B. Essex et al. (2020) [19]	Measuring water-related indicators to meet clean water and sanitation SDGs	Proposed a national blueprint framework (NBF) with 24 water-related indicators
María C et al. (2020) [20]	Overview of challenges in wastewater management	Analysis of biomarkers in wastewater to assess the health of the population
Spirandelli et al. (2019) (2020) [21]	On-site decentralized waste water management	Gap analysis to show deficiencies in on-site wastewater management
Congcong et al. (2020) [22]	Real-time control of urban water cycle	Cyber physical system
Nie et al. (2019) [5]	Sustainable smart city wastewater treatment	Big data analytics and IoT
Sathishkumar et al. (2020) [6]	Nutrient water supply prediction for fruit production	Artificial Neural Networks (ANNs)
Jeong et al. (2020) [23]	Comparative evaluation of urban water management	Water Metabolism Framework (WMF)
Landa-Cansigno et al. (2020) [24]	Efficiency evaluation of water recycling techniques	Framework of urban water metabolism (UWM) and water–energy–pollution nexus (WEPN)
Ojagh et al. (2021) [25]	Improvement of prediction accuracy in an IoT-based monitoring system	Hybrid edge–cloud preprocessing framework

Vibhas Sukhwani et al. [17] discussed the development of smart urban–rural linkages in a metropolitan area using a water–energy–food nexus-based conceptual approach. To answer this necessity, they presented a conceptual knowledge framework (KCF) that provides an overview of the water supply flow within the NMA between urban and rural areas. The study shows feasible guidance for intelligently linking future developments in smart cities with the adjacent Rurban Cluster based on the developed framework. The study also visualized the water, energy, and food linkages between the urban and rural divide.

H. K. Pandey et al. [18] suggested the GIS and water quality index for groundwater quality assessments of a smart city. A water quality index and geographic information system was used to determine groundwater samples' physico-chemical parameters for drinking purposes. The contamination level in the area was exacerbated by groundwater exploitation, urban planning, and anthropogenic practices.

B. Essex et al. [19] introduced the national blueprint framework (NBA) for the Sustainable Development Goals to monitor progress on water-related goals in Europe. The 17 Sustainable Development Goals (SDGs), endorsed by 169 countries, face significant obstacles in adoption by national governments. A national blueprint framework (NBF) with 24 water-related indicators based on SDG Six, each with a specific goal, was created.

María C et al. [20] inferred wastewater management using paradigm shifts and current challenges. Wastewater is a major environmental and public health concern, and since ancient times, its management has been a relentless task. In recent decades, drainage analysis has grown exponentially. This paper offered a global review of growing wastewater science to recognize existing problems and paradigm shifts. Wastewater studies can answer global issues, such as the public approval of water conservation or access for almost one-third of the world's population to basic sanitation.

The authors of [21] developed decentralized wastewater based on a management policy gap analysis. On-site wastewater treatment (OWTS) schemes have been planned for the decentralization of wastewater on site. The study indicates a lack of coordination between land use and water baseline preparation, efficiency priorities, system inventories, public outreach, homeowner education, routine inspections, and maintenance processes.

In [22], the author suggests a cyber-physical systems management framework (CPSMF) for real-time control of the urban underwater cycle. Vital infrastructure, or urban life functioning, needs to be installed in the urban water cycle (UWC), including the water supply systems and the urban drainage system (UDS). This paper suggests a CPS-based management framework that allows control, interoperability, and automated optimization of the UWC to maximize the benefits from CPSs.

The author of [5] introduces Big Data analytics and the IoT into operation safety management underwater. An intelligent society such as a smart city is defined by a place where people live well, plan their lives long term, ensure sustainability, and do the least harm to the physical environment by ICTs. This paper analyses the Supervisory Controller and Data Acquirement (SCADA) approach to sustainable smart city water treatment based on the Internet of Things and Big Data Analytics. Big data analysis is a new technological term implying the processing of vast volumes of relevant data from installed IoT sensors to monitor the device's physical status, utilization, and efficiency.

Seongpil Jeong et al. [23] used a Water Metabolism Framework (WMF) to evaluate urban water management in a comparative analysis of three regions. In Korea and elsewhere, sustainable water conservation focuses on water conservation and reuse, as the climate and environmental transitions raise the importance of water insecurity. In Ulsan, water is being abstracted. The river's water supply is less sustainable and more vulnerable to weather threats than Seoul, thus making Ulsan's water infrastructure less sustainable and more vulnerable.

Oriana Landa-Cansigno et al. [24] discussed the integrated framework of the urban water metabolism (UWM) and the water–energy–pollution nexus (WEPN) for an efficiency evaluation of water recycling techniques. This paper analyses metabolic efficiency and its effect on a variety of centralized and decentralized water reuse policies and the WEPN on integral UWSs. The findings suggest a metabolism measurement of the output in a complex system such as an UWS will illustrate the degree of the interactions among the nexus (e.g., water, energy, and pollution) components.

IoT-based systems employed in applications similar to wastewater management systems, e.g., air quality monitoring systems, exhibit a loss in accuracy compared to the traditional measurement systems due to missing values and noisy data. The authors of [25] improved the prediction accuracy of a real-world IoT-based air quality monitoring system using a hybrid edge–cloud preprocessing framework.

3. Proposed Model: IoT-Based Wastewater Management System (IoT-WMS)

The prospect of water shortages is worrying as population growth rises. This has sparked the notion of wastewater reuse and recycling. Sensors may therefore be used for processing and monitoring at various stages of wastewater management. A comprehensive literature survey leads the research for developing an IoT-WMS framework. The IoT-WMS concentrates on cloud security using blockchain technology for the intelligent wastewater management schemes followed by smart cities. This IoT-WMS proposes a trading system based on the use of blockchain rewards for wastewater recycling. Every household/industry in the smart city enables the IoT-based wastewater management strategy with sensors and actuators. The basic conceptual structure of the IoT in wastewater management for smart cities is shown in Figure 1.

Figure 1 shows the wastewater management cycle with efficient cloud data visualization for decision making. The decision support system performs token (cryptocurrency) allocation to households/industries regarding the volume of recycled wastewater. Based on their requirement to reach a minimum threshold volume, households/industries later resell these tokens. In a smart contract, the guidelines for the token exchange are established. Data stored on a blockchain-enabled cloud give inviolable auditing. The smart contracts often provide an automatic tracking framework with a secure cloud. Supervised and unsupervised learning algorithms are used to detect the manipulation of information on wastewater recycling in IoT meters by individuals to ensure the robustness of this model. Effective home automation allows the best usage of water and thereby increases the performance of the water delivery system and its services. For anomaly identification, this study utilizes a polynomial regression analysis algorithm. This anomaly monitoring model has been implemented to detect theft in energy consumption power meters. The time-series data are the meter readings, so a sequential learning model has been considered in this work. The IoT helps gain access to knowledge and makes significant decisions by obtaining various sensor values such as soil moisture, water levels, etc.

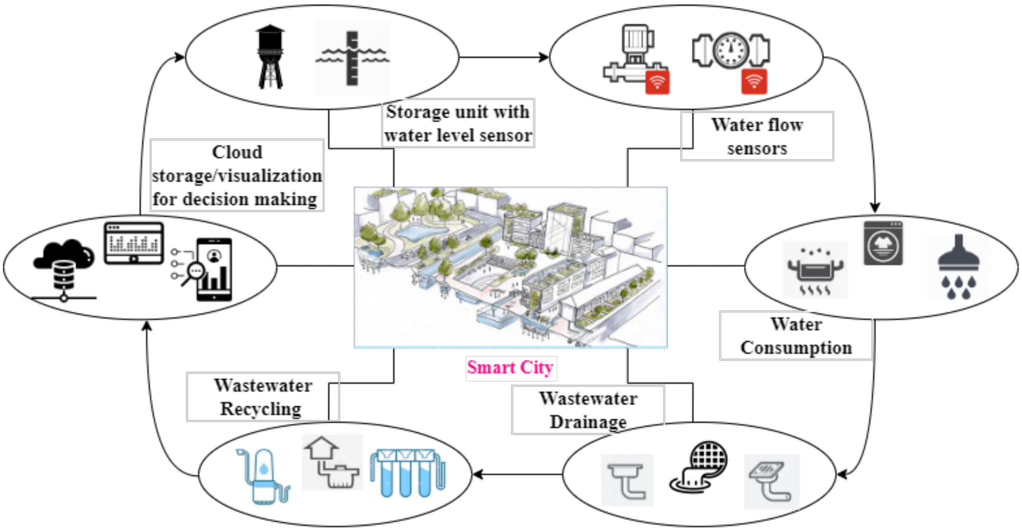

Figure 1. Domestic wastewater management cycle in smart cities.

3.1. Wastewater Management Architecture with Blockchain Technology

The smart wastewater management framework based on blockchain technology consists of five layers, as shown in Figure 2.

The first layer, named the sensor layer, establishes the various IoT sensors for monitoring water usage and wastewater recycling. The data captured through these sensors are considered in the second layer called the data collection layer. In this layer, various industry/household facilities from layer 1, such as pipelines attached with level gauges, water meters attached water storage tanks, and smart wastewater treatment units fitted with IoT-based intelligent objects, are able to sense, track, analyze, acquire, and interact with data concerning the level of water storage, the quantity of water usage, the volume of wastewater generation, and its recycling volume. The gathered information is further transmitted to the third layer, the edge computing layer attached with edge nodes/smart gateways, through accessible internet services such as WiFi, 4G, and 5G for computation, decision making, collaborative filtering, and transient data storage over a preconfigured period of time. Using the edge nodes, the aggregated data items are validated through smart contracts and added to the blockchain. The edge nodes hand over the validated data units to the cloud server in the fourth layer: the wastewater blockchain located on cloud-based servers responsible for collecting, storing, processing, monitoring, and managing blockchain-technology-assisted security operations handling massive data produced from different IoT-enabled smart cities. In the fifth layers, frameworks for the management and monitoring of wastewater treatment for recycling and reuse are present. Through smart contracts, all parties interested in smart city wastewater management and monitoring are capable of querying the stored information in the blockchain-enabled cloud. For example, authorized people can access and visualize the data for decision making.

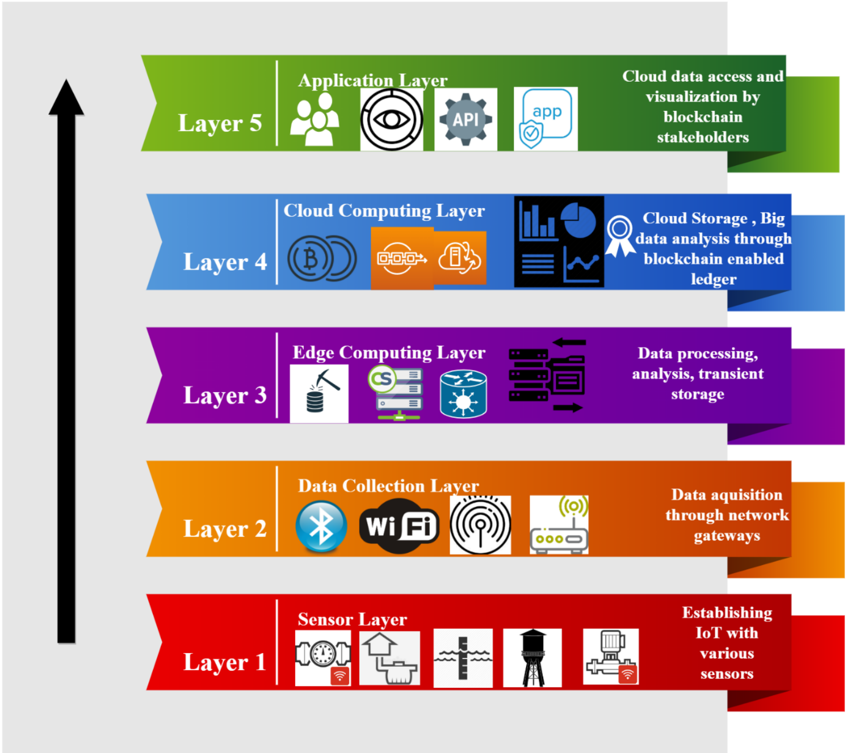

Figure 2. Architectural diagram of wastewater management with blockchain technology.

Conceptual Workflow of IoT-WMS

The IoT-WMS framework's main objective is to oversee and manage the volume of smart city wastewater recycling remotely using a wastewater treatment unit that extracts hazardous chemical liquids maintained by each household/industry in a smart city. The following are a detailed description of various phases involved in the above process:

Phase 1:

Smart IoT sensors and actuators are mounted on various observation decks and administration devices related to water flow and level monitoring, water collection units, and wastewater treatment units.

Phase 2:

The deployed IoT devices will identify, process, and collect the water storage level, usage volume, and wastewater recycling in wastewater treatment. The gathered information is communicated to edge devices/nodes through smart gateways with acceptable technological innovations such as 4G, 5G, and WiFi.

Phase 3:

The edge nodes perform the aggregation of the information gathered by various database objects. Furthermore, by executing the authentication process, transient data will be stored on the blockchain. In parallel, for real-time analytics and decision making, it activates data processing at the edge nodes.

Blockchain is a data structure that holds a database from distributed communication. Blockchain comprises four main elements that make up its entire architecture. The first element, the decentralized network, is a peer-to-peer (P2P) link between sensor nodes. The interactions which happen in the system are managed by all the nodes. The next element, the distributed ledger, is an eternal, incorruptible, and publicly transparent archive distributed within network nodes with strengthened traceability. According to a consensus algorithm, the third element, trades, is checked and confirmed through peers in the respective network. This assists the ledger in remaining consistent, which guarantees the ledger modification when those network members accept it. The fourth element, smart contracts, defines the type of transactions that take place within the network. It helps to exchange tokens/rewards between stakeholders, apply strategies, or define resource user privileges.

As the application framework for implementing approved blockchain networks, Hyperledger Fabric has been used [26–28]. It is an open-source, certified, distributed application framework built on blockchain that enables developers to create and deploy distributed services. The Composer tool is applicable for constructing the logic of the management platform. Smart contracts are distributed on all endorser nodes of the network in a Fabric network, and the peers check the transfers as shown in Figure 3. If the transaction is officially accepted, it is attached to the ledger and then exchanged with all network nodes. An authorized blockchain guarantees that when they directly reach the network, sectors are validated. Except for Bitcoin or Ethereum, Hyperledger Fabric employs a Kafka-based consensus rather than Proof-of-Work due to its computation cost. Proof-of-Work gives faith in a world of trustlessness. The application scenario in this research has a regulatory model for issuing tokens and rewards, so Proof-of-Work is not needed in this context.

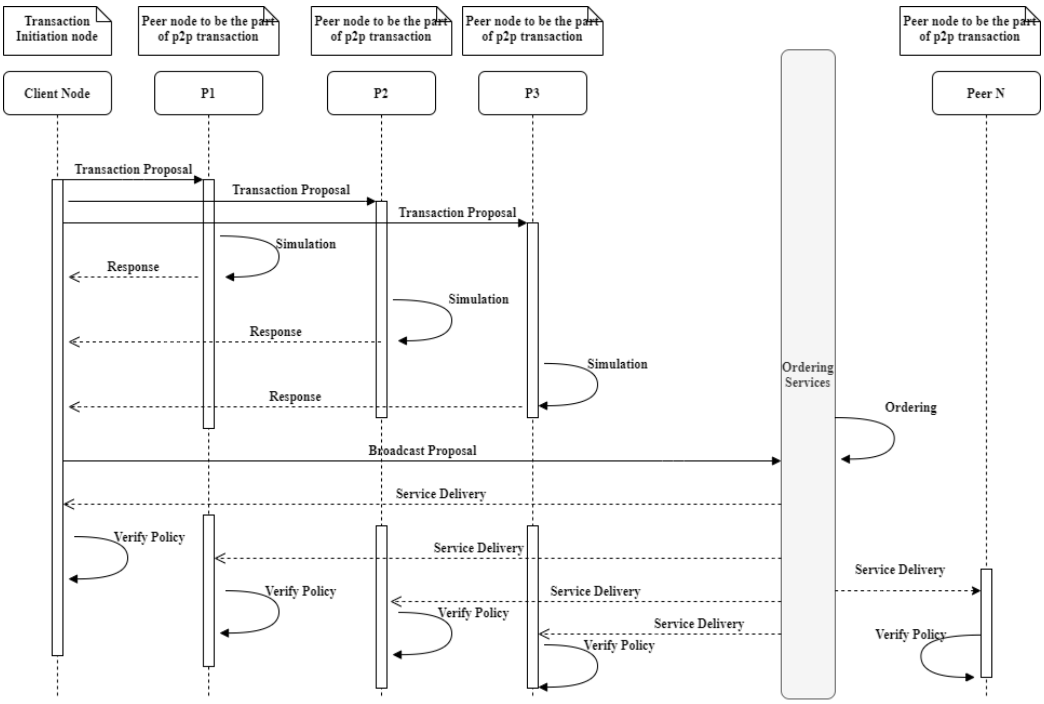

Figure 3. Flow of Hyperledger transaction.

Phase 4:

Each node responsible for validating data units earns a reward for every block to be authenticated and mined. These rewards (virtual tokens) are traded for different benefits such as obtaining concessions on energy bills, tariffs, taxes, etc. Incentives are then incorporated into the scheme to encourage clients to support the wastewater management program in the smart city and invest in it.

Phase 5:

Using smart contracts, the validated data blocks can be submitted to cloud servers and logged to the blockchain. The cloud infrastructure can provide big data analysis and analytics capabilities on the collected data for future monitoring and decision making.

Phase 6:

Ultimately, to evaluate water consumption, the volume of toxic chemical liquids generated, treated, and disposed of by each household/industry in smart cities, various monitoring and management applications need to be created. In this phase, tokens, referred to in the Hyperledger Composer as tradable cryptocurrencies, are distributed to households/industries in the smart city on the basis of their wastewater reuse output. The most productive participant is considered a zero liquid spill strategy and a hundred percent wastewater is reused in its unit.

$$Q_f = \frac{V_r}{V_p}, \text{for every member unit in smart city} \tag{1}$$

$$Q_f^{'} = q(h, s, o, p), \tag{2}$$

$$T = a_1 * Q_f + a_2 * Q_f^{'}, \tag{3}$$

where Q_f and $Q_f^{'}$ denote the quantity and quality factors, respectively. T represents the number of tokens to be issued, while a_1 and a_2 are constant values above the threshold values. Tokens are given in compliance with Equations (1)–(3), on the basis of the quality and quantity of wastewater recycling. For each participant, the threshold criterion for wastewater recycling differs due to the complexities in treating the various forms of toxins. When the participant surpasses the threshold, it can trade tokens to other participants who have not reached the ceiling. Similarly, tokens are often issued to promote greater purity of filtered water based on efficiency.

3.2. Anomaly Detection

Anomaly detection is inevitable in IoT-WMS because it detects fraud tampering in the wastewater management sensor readings. This research extends the study with an algorithm as follows:

Polynomial Regression Analysis

Polynomial regression analysis is an algorithm that forms a relationship between two variables, such as the input variable (independent), I, and the output variable (dependent), O. The regression analysis relationship is defined as a polynomial of I in x-th degree, as shown in (4):

$$O_m = \tau + \sum_{i=1}^{x} \mu_i I_m^x + \epsilon_m, \tag{4}$$

where τ is the threshold reading value, μ_i denotes the regression factor for $i \in \{1, 2, 3, \ldots, x\}$, and ϵ_m represents the error rate with $m \in \{1, 2, 3, \ldots, n\}$ for n samples. If the squared difference between the real value and the expected value approaches the threshold set based on training results, the analysis model predicts the abnormality. The proposed IoT-WMS improves the quality of recycled water distributed in smart cities and achieves a high wastewater recycling rate and efficiency ratio, a lower moisture content ratio, improved wastewater reuse, and a higher prediction ratio.

4. Simulation Results and Discussion

The proposed IoT-WMS model monitors the recycled wastewater distribution in a smart city. Various parameters such as the wastewater recycling rate, the efficiency ratio, the moisture content ratio, the wastewater reuse ratio, and the prediction ratio have been considered using the proposed IoT-WMS method. The number of devices used for numerical simulations ranged from 5 to 30 in increments of 5. Each of these devices is assumed to have the capability of supporting up to 10 sensors. The simulation results averaged several random placements of sensors in a two-dimensional space. The devices are distributed in various stages of the wastewater management system, e.g., storage units, drainage units, recycling units, and water consumption units. A blockchain-based incentivization method is provided to various stakeholders in a model metropolitan area and its effect on the above parameters has been analyzed and compared with several existing approaches. Periodic monitoring of these parameters is performed using a cloud-based IoT system.

4.1. Wastewater Recycling Rate

The wastewater treatment method relies on different factors such as wastewater temperature, water velocity, water flow, and pH. The productivity of the treatment plant improves if these parameters are kept within the necessary limits. These parameters must be carefully controlled to handle water efficiently. The IoT handles the wastewater. The IoT is a network that can link all devices embedded in electronic systems. Electronic IoT systems can interact and transfer information with each other. Several physical parameters can be tracked and communicated to linked equipment such as cell phones and laptops through different channels through sensors in wastewater treating plants, such as temperature, flow rate, and water level sensors in various tanks. When the sensors sense anomalies above the acceptable thresholds of the physical parameters, the IoT can send a warning to the plant operator via a message or an e-mail and take a control action. Figure 4 shows the wastewater recycling rate for our proposed approach as a function of the number of IoT devices deployed within a metropolitan area. The recycling rate is also compared with several state-of-the-art systems and it has been shown that the performance of the proposed IoT-WMS system is superior to the existing approaches. Moreover, the recycling rate improves as the number of deployed devices increases. In other words, the availability of more measurements and quality feedback helps improve the recycling rate.

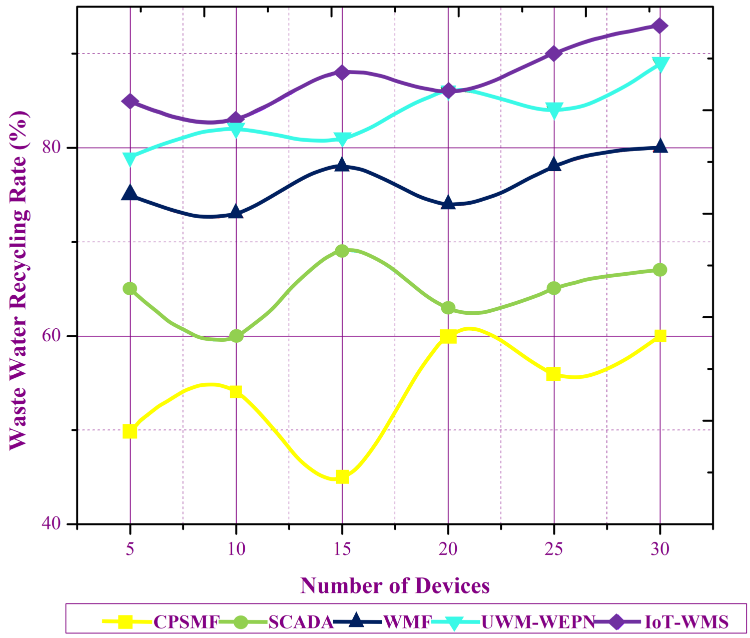

Figure 4. Wastewater recycling rate.

4.2. Efficiency Ratio

Effective wastewater collection (WC) is a key factor in smart cities' service. Smart cities based on an integrated framework of new technologies can use the Internet of Things (IoT). Monitoring devices could be used as an assistive technology in wastewater collection to provide a high quality of service (QoS). The following IoT elements are directly integrated into ITS and waste disposal control systems: (i) RFID, (ii) sensors, (iii) camera, and (iv) actuators. We suggest IoT-WMS in this paper as an innovative solution to effectively store wastewater in smart cities. It includes a data management model for real-time monitoring of pipes to capture wastewater levels and leverage complex pathways.The system manages inadequate wastewater collection in inaccessible areas in smart cities. Surveillance cameras are used to capture the trouble areas and to supply the the controllers with evidence. The wastewater treatment scheme aims to provide the people of a smart city with a high standard of operation. Figure 5 shows the efficiency ratio for our proposed approach as a function of the number of IoT devices deployed within a metropolitan area. The efficiency ratio is also compared with several state-of-the-art systems and it has been shown that the performance of the proposed IoT-WMS system is superior to the existing approaches. Moreover, the efficiency ratio improves as the number of deployed devices increases. In other words, the availability of more measurements and quality feedback helps improve the efficiency of the wastewater management system.

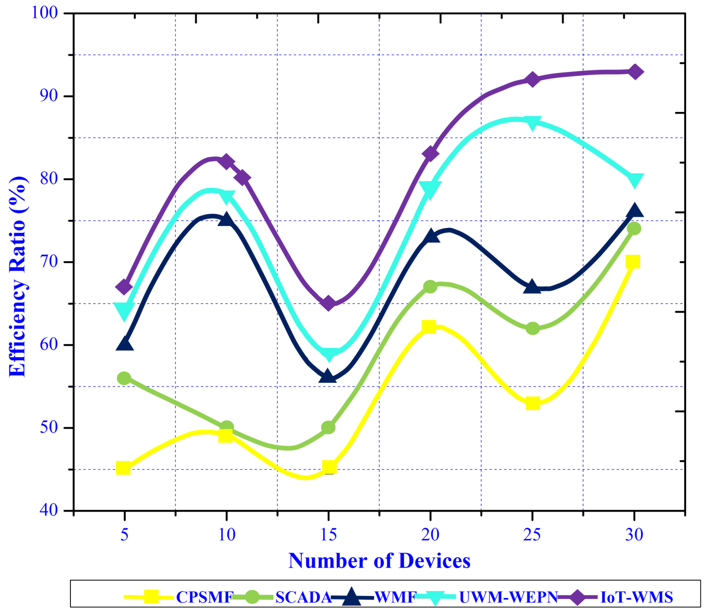

Figure 5. Efficiency ratio.

4.3. Moisture Content Ratio

The proposed IoT-WMS covers numerous features such as GPS-based remote temperature and moisture sensing and irrigation equipment. It utilizes wireless sensor networks to record water characteristics and environmental factors continuously. There are multiple sensor nodes in a smart city at various points. These parameters are tracked from any remote computer or internet service, and interface sensors with IoT perform the operations. This is mainly based on reducing water waste and minimizing manual work in the irrigation sector to save smart cities' time, resources, and electricity. The system proposes to allow farmers to continually track the water levels in water tanks and humidity in the field by remotely monitoring the supply on the internet. When the humidity falls below a certain level, drip irrigation will be automatically enabled, thereby ensuring maximum irrigation via the internet. Figure 6 shows the moisture content ratio as a function of the number of devices. It can be seen that the moisture content ratio is the lowest for our proposed scheme, with performance of our scheme closest to the UWM-WEPN approach. Furthermore, increasing the number of devices yields a lower moisture content ratio.

4.4. Wastewater Reuse Ratio

Blockchain or distributed ledger is a promising emerging platform that facilitates the use of a lack of water supplies to store and maintain. The concept of blockchain reconciliation may be a perfect case of inventive reasoning and opportunities for cooperation intended to examine the foundational problem of scarcity. The distributed ledger should be used not only for water use and control of water recovery but can also be used to promote wastewater sharing and rainwater harvesting for a more prosumer market. Blockchain could also be used to develop peer-to-peer water trading networks. Prosumers may receive wastewater for further treatment, reuse, recycling, and disposal over the water processing life cycle. Blockchain will radically change the way of handling water supplies, from the diligent use of renewable and fresh water and water use settlement and payment collection to water use and frequent reporting. Figure 7 shows the wastewater reuse ratio as a function of the number of devices. The wastewater reuse ratio is the best for our proposed system relative to other recent approaches. The performance of UWM-WEPN is better than the rest of the approaches, while CPSMF shows a poor relative performance.

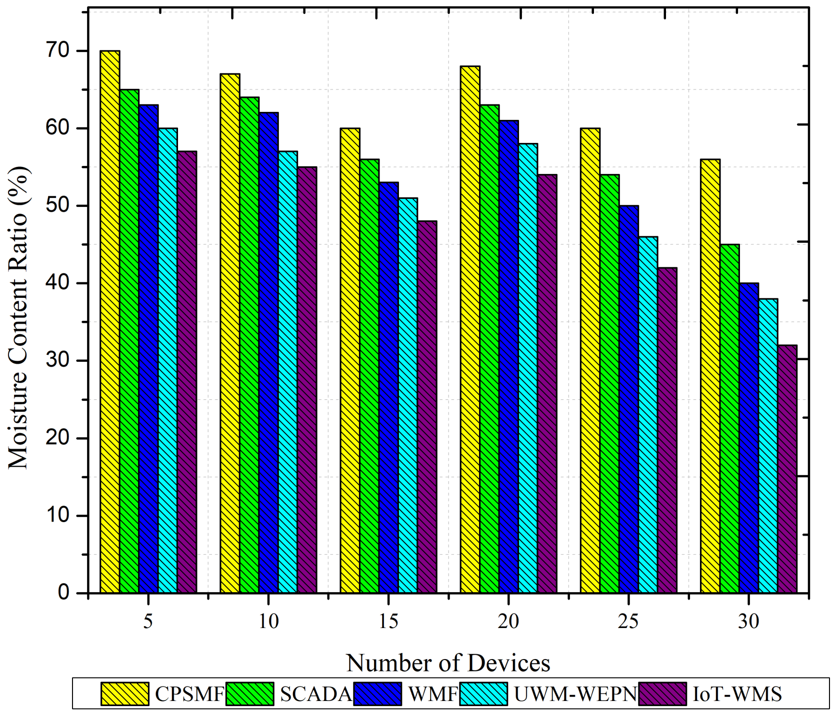

Figure 6. Moisture content ratio.

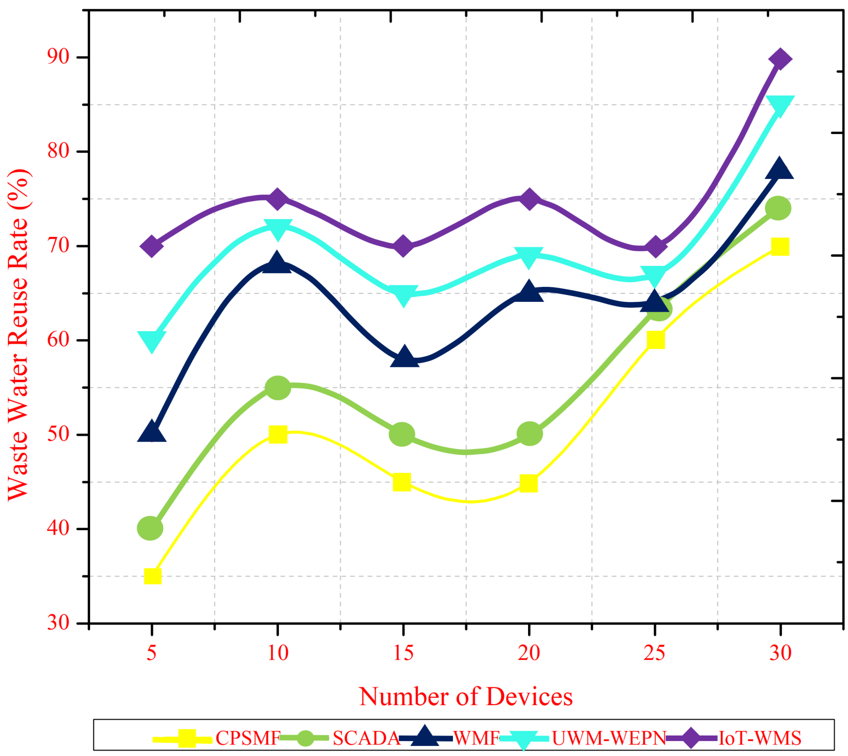

Figure 7. Wastewater reuse ratio.

4.5. Prediction Ratio

It is necessary to control water in any part of its cycle in smart city water management: from freshwater abstraction, pretreatment, delivery, use, and collection to post-treatment. By removing pollution and changing the way to treat wastewater, the water quality will be improved. To ensure water safety, IoT-allowed monitoring systems could be deployed. Wireless sensors and the anomaly detection algorithm help anticipate leaks, maximizing resources, sales, running costs, and pipe repair facilities. Through blockchain technologies, city companies and city municipalities can monitor water delivery and use in real time. Through this proposed method, it is possible to track the water quality. Water filtration devices are used to guarantee the water is of good quality, thus reducing water loss. Predictive management methods used in water plants ensure that problems contributing to the risk of water pipes failing are evaluated rapidly and efficiently. Figure 8 shows the prediction ratio. The prediction ratio shows considerable improvement with an increasing number of IoT devices for all the considered approaches. Furthermore, the predictive performance of the proposed IoT-WMS systems is better than the rest of the approaches. The CPSMF approach shows some promise for lower numbers of devices but its performance deteriorates before improving as the IoT devices transition from a moderate value to a larger number.

The proposed IoT-WMS improves the quality of recycling water distributed in smart cities and achieves a high wastewater recycling rate and efficiency ratio, a lower moisture content ratio, improved wastewater reuse, and a better prediction ratio compared to the cyber-physical systems management framework (CPSMF), the supervisory controller and data acquirement (SCADA) approach, the Water Metabolism Framework (WMF), the urban water metabolism method (UWM), and the water–energy–pollution nexus (WEPN) method.

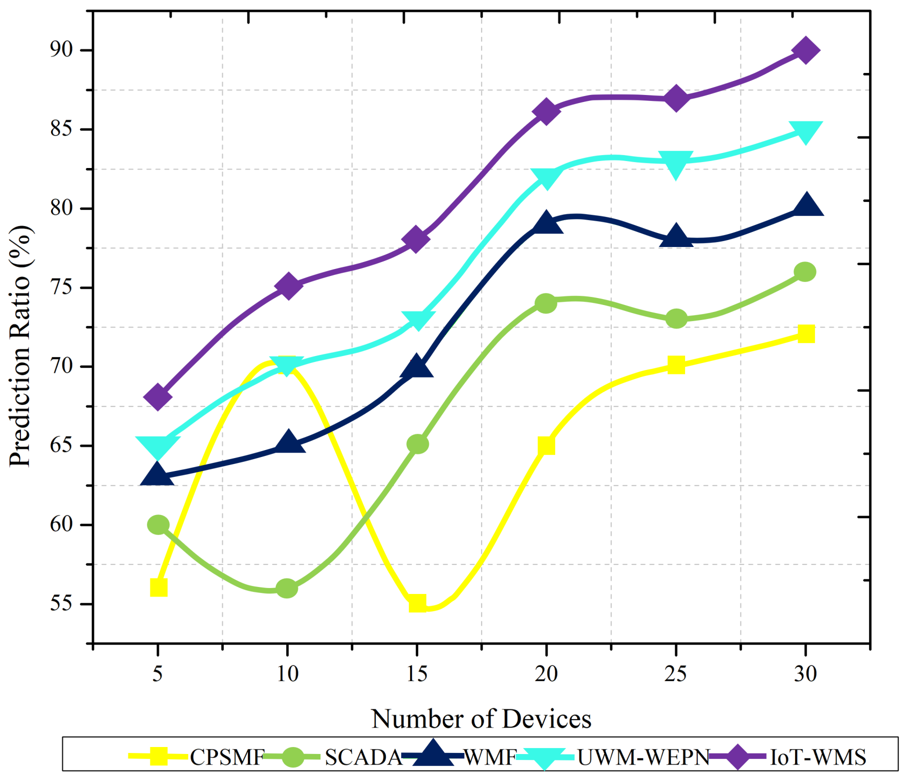

Figure 8. Prediction ratio.

5. Conclusions

A detailed literature survey helped us to establish a smart wastewater collection system for smart cities, namely the IoT-WMS system concentrated on cloud protection and leveraging blockchain technologies. This IoT-WMS uses a trading scheme focused on the recovery of wastewater using blockchain incentives. Sensors and actuators make the IoT-based wastewater management strategy available for all households/industries in the smart city. Compared to existing models, the proposed IoT-WMS for wastewater treatment and recycling water quality in smart cities achieved a high wastewater recycling rate of 96.3%, an efficiency ratio of 88.7%, a low moisture content ratio of 32.4%, an increased wastewater reuse of 90.8%, and a prediction ratio of 92.5%. The proposed approach has limitations when it comes to the interworking of such systems deployed by several metropolitan and/or rural areas. A framework to incentivize wastewater quality improvement is more useful if it allows for reward tokens to be redeemable across various industrial sectors and facilities. A future extension of this study is to expand the system with in-depth learning assistance for wastewater management in smart cities using deep learning technology.

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References

1. Srivastava, A.; Grotjahn, R.; Ullrich, P.A.; Risser, M. A unified approach to evaluating precipitation frequency estimates with uncertainty quantification: Application to Florida and California watersheds. *J. Hydrol.* **2019**, *578*, 124095. [CrossRef]
2. Khan, M.T.R.; Jembre, Y.Z.; Ahmed, S.H.; Seo, J.; Kim, D. Data freshness based AUV path planning for UWSN in the internet of underwater things. In Proceedings of the 2019 IEEE Global Communications Conference (GLOBECOM), Waikoloa, HI, USA, 9–13 December 2019; pp. 1–6.
3. Yaqub, M.A.; Ahmed, S.H.; Bouk, S.H.; Kim, D. Towards energy efficient duty cycling in underwater wireless sensor networks. *Multimed. Tools Appl.* **2019**, *78*, 30057–30079. [CrossRef]
4. Moon, E.; Khan, M.T.R.; Park, H.; Ahmed, S.H.; Lee, S.; Kim, D. OMRI–MAC: Optimized multi-transmission receiver-initiated MAC in underwater wireless sensor networks. *Wirel. Pers. Commun.* **2019**, *107*, 1491–1505. [CrossRef]
5. Nie, X.; Fan, T.; Wang, B.; Li, Z.; Shankar, A.; Manickam, A. Big data analytics and IoT in operation safety management in under water management. *Comput. Commun.* **2020**, *154*, 188–196. [CrossRef]
6. Sathishkumar, V.; Venkatesan, S.; Park, J.; Shin, C.; Kim, Y.; Cho, Y. Nutrient water supply prediction for fruit production in greenhouse environment using artificial neural networks. In *Basic & Clinical Pharmacology & Toxicology*; Wiley: Hoboken, NJ, USA, 2020; Volume 126, pp. 257–258.
7. Venkatesan, S.; Sathishkumar, V.; Park, J.; Shin, C.; Cho, Y. A Prediction of nutrition water for strawberry production using linear regression. *Int. J. Adv. Smart Converg.* **2020**, *9*, 132–140.
8. Sundarasekar, R.; Shakeel, P.M.; Baskar, S.; Kadry, S.; Mastorakis, G.; Mavromoustakis, C.X.; Samuel, R.D.J.; Gn, V. Adaptive energy aware quality of service for reliable data transfer in under water acoustic sensor networks. *IEEE Access* **2019**, *7*, 80093–80103. [CrossRef]
9. Gupta, O.; Goyal, N.; Anand, D.; Kadry, S.; Nam, Y.; Singh, A. Underwater networked wireless sensor data collection for computational intelligence techniques: Issues, challenges, and approaches. *IEEE Access* **2020**, *8*, 122959–122974. [CrossRef]
10. Khan, W.A.; Khan, M.I.; Kadry, S.; Farooq, S.; Khan, M.I.; Abbas, S.Z. Transportation of water-based trapped bolus of SWCNTs and MWCNTs with entropy optimization in a non-uniform channel. *Neural Comput. Appl.* **2020**, *32*, 13565–13576. [CrossRef]
11. Salami, A.F.; Adedokun, E.A.; Al-Turjman, F.; Bello-Salau, H.; Sadiq, B.O.; Dogo, E.M. Explorative analysis of AUV-aided cluster-based routing protocols for Internet of intelligent underwater sensors. In *Drones in Smart-Cities*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 143–187.
12. Deebak, B.D.; Al-Turjman, F. Aerial and underwater drone communication: Potentials and vulnerabilities. In *Drones in Smart-Cities*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 1–26.
13. Krishnaraj, N.; Elhoseny, M.; Thenmozhi, M.; Selim, M.M.; Shankar, K. Deep learning model for real-time image compression in Internet of Underwater Things (IoUT). *J. Real-Time Image Process.* **2020**, *17*, 2097–2111. [CrossRef]
14. Shankar, K.; Elhoseny, M.; Shankar, K.; Elhoseny, M. An optimal singular value decomposition with LWC-rectangle block cipher based digital image watermarking in wireless sensor networks. In *Secure Image Transmission in Wireless Sensor Network (WSN) Applications*; Springer: Cham, Switerland, 2019; pp. 83–98.

15. Saračević, M.; Adamović, S.; Maček, N.; Elhoseny, M.; Sarhan, S. Cryptographic keys exchange model for smart city applications. *IET Intell. Transp. Syst.* **2020**, *14*, 1456–1464. [CrossRef]
16. Amin, F.; Abbasi, R.; Mateen, A.; Ali Abid, M.; Khan, S. A Step toward Next-Generation Advancements in the Internet of Things Technologies. *Sensors* **2022**, *22*, 8072. [CrossRef] [PubMed]
17. Sukhwani, V.; Shaw, R. A Water-Energy-Food Nexus based Conceptual Approach for Developing Smart Urban-Rural Linkages in Nagpur Metropolitan Area, India. *IDRiM J.* **2020**, *10*, 1–22. [CrossRef]
18. Pandey, H.; Tiwari, V.; Kumar, S.; Yadav, A.; Srivastava, S. Groundwater quality assessment of Allahabad smart city using GIS and water quality index. *Sustain. Water Resour. Manag.* **2020**, *6*, 28. [CrossRef]
19. Essex, B.; Koop, S.; Van Leeuwen, C. Proposal for a national blueprint framework to monitor progress on water-related sustainable development goals in Europe. *Environ. Manag.* **2020**, *65*, 1–18. [CrossRef] [PubMed]
20. Villarín, M.C.; Merel, S. Paradigm shifts and current challenges in wastewater management. *J. Hazard. Mater.* **2020**, *390*, 122139. [CrossRef] [PubMed]
21. Spirandelli, D.; Dean, T.; Babcock, R., Jr.; Braich, E. Policy gap analysis of decentralized wastewater management on a developed pacific island. *J. Environ. Plan. Manag.* **2019**, *62*, 2506–2528. [CrossRef]
22. Sun, C.; Puig, V.; Cembrano, G. Real-time control of urban water cycle under cyber-physical systems framework. *Water* **2020**, *12*, 406. [CrossRef]
23. Jeong, S.; Park, J. Evaluating urban water management using a water metabolism framework: A comparative analysis of three regions in Korea. *Resour. Conserv. Recycl.* **2020**, *155*, 104597. [CrossRef]
24. Landa-Cansigno, O.; Behzadian, K.; Davila-Cano, D.I.; Campos, L.C. Performance assessment of water reuse strategies using integrated framework of urban water metabolism and water-energy-pollution nexus. *Environ. Sci. Pollut. Res.* **2020**, *27*, 4582–4597. [CrossRef]
25. Ojagh, S.; Cauteruccio, F.; Terracina, G.; Liang, S.H. Enhanced air quality prediction by edge-based spatiotemporal data preprocessing. *Comput. Electr. Eng.* **2021**, *96*, 107572. . [CrossRef]
26. Attia, O.; Khoufi, I.; Laouiti, A.; Adjih, C. An IoT-blockchain architecture based on hyperledger framework for health care monitoring application. In Proceedings of the NTMS 2019-10th IFIP International Conference on New Technologies, Mobility and Security, Canary Islands, Spain, 24–26 June 2019; pp. 1–5. [CrossRef]
27. Corradini, E.; Nicolazzo, S.; Nocera, A.; Ursino, D.; Virgili, L. A two-tier Blockchain framework to increase protection and autonomy of smart objects in the IoT. *Comput. Commun.* **2022**, *181*, 338–356. [CrossRef]
28. Capocasale, V.; Gotta, D.; Musso, S.; Perboli, G. A Blockchain, 5G and IoT-based transaction management system for Smart Logistics: An Hyperledger framework. In Proceedings of the 2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC), Madrid, Spain, 12–16 July 2021; pp. 1285–1290. [CrossRef]