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Review

Towards Digitalization of Water Supply Systems for Sustainable Smart City Development—Water 4.0

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Abstract: Urban water supply systems are complex and dynamic in nature, and as a result, can be considered complex to manage owing to enhanced urbanization levels, climate change, growing and varying consumer demands, and limited water resources. The operation of such a system must be managed effectively for sustainable water supply to satisfy the growing consumer demand. This creates a need for intelligent systems for the purposes of operational management. In recent years, computing technologies have been applied to water systems to assist water utilities in addressing some of these problems. Unfortunately, previous ICT solutions have not been able to provide the necessary support for applications to deal with the dynamics of water supply system environments. With the increasing growth in technology, the water sector is moving to the full phase of digitalization to enhance the sustainability of systems. Thus, a new industrial revolution in the water context (Water 4.0) is being researched. This is referred to as Water 4.0, which offers better possibilities to enhance the sustainability of water supply system operations. This paper presents an overview of Water 4.0 and its applications in enhancing water supply system operations. Key features of Water 4.0 are discussed. Furthermore, challenges and future opportunities offered by technology for sustainable operation of municipal water services are discussed.

Keywords: AI; cyber physical system; ICT; Industry 4.0; Internet of Things; Water 4.0; water loss; water supply system

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1. Introduction

Water is an important component of economies today and is needed in nearly all modes of production. It is a fundamental resource utilized in virtually every modern industrial process and provides an essential element for urban development across the country. Hence, it is important to ensure that everyone has access to clean and pollution-free water, which is a duty of the municipal water service or water utility. Water utilities are saddled with the responsibilities of supplying potable water to end users in accordance with objective six of the United Nation's sustainable development goals. This is achieved through the use of water supply systems (WSS). WSS operations require the delivery of potable water to end consumers via a vast and complex network of distribution piping systems. Water utilities worldwide face increasing challenges to ensure sustainable water distribution to the end consumer. These challenges stem from burgeoning populations, the dynamic nature of water supply distribution systems owing to the effect of climate change and consumer demand uncertainties, as well as the frequent level of water losses in systems. Modern water supply networks are complicated, dynamic in nature and hard to manage owing to the stochastic nature of water demand. They comprise a complex network of pipelines (see Figure 1) buried underground for several years and are not readily accessible. Thus, due to ageing, corrosion issues and third-party damage, cracks occur along the pipes, which causes loss of significant volumes of water. One of the major problems affecting water supply system operations is water loss due to leaking pipes. Even in a new system, background losses may occur at the pipe fittings and cross-connections point and run continuously through the entire lifespan of the piping network [1,2]. Since they are underground large structures and not readily accessible, monitoring becomes a serious challenge. In a severe situation, the problem becomes more complex when leaks occur at several points along the pipes. In fact, it is crucial to localize pipe leaks as quickly as possible after the occurrence and pinpoint the leaks' hotspots to perform active maintenance in the region of high leak occurrence in the network. On an annual basis, there is a dramatic increase in the investment cost for leak detection and repair [3]. This is because its maintenance rate increases exponentially once a pipe's length starts to require maintenance [4].

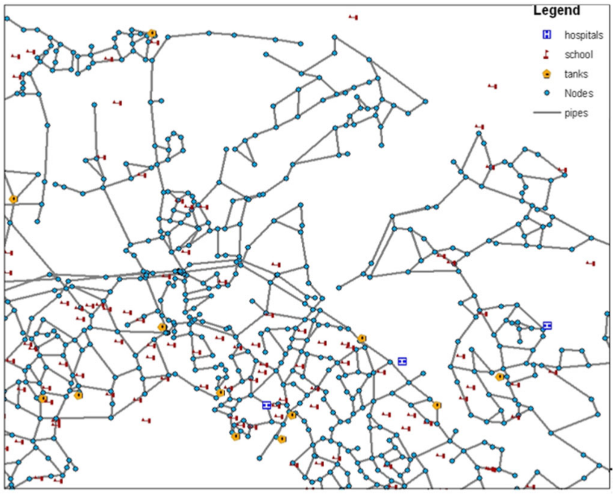

Figure 1. Schematics of a water distribution piping network.

Other issues affecting the smooth operation of water supply systems include pressure control, water demand management, pump scheduling, operational planning and control, and water security as reported in [5], among others. Furthermore, the financial losses, improved maintenance cost to repair leaky pipes and the increased energy expenditure required to feed the leaks are major problems caused by water losses [6–10]. Considering the latter, the occurrence of a leak requires more energy to maintain desired service levels [6,7]. That is, more energy is required to pump water to meet specific demand at a node. This escalates the cost of energy due to extra pumping of water. Consequently, a relatively high cost associated with pumping due to leaks is one of the problems caused by water losses. Thus, the operation of water supply distribution systems usually requires a large amount of energy, which varies with respect to the characteristics of the region served [11]. For instance, in the United States it was estimated that about 10 billion kWh of power generated is budgeted towards water losses annually [12]. The water quality may also be compromised. This is because leaks introduce infections into a water supply system operating under low-pressure conditions [9,13]. This increases the risk of water quality deterioration, which also prompts the need to assess the water contamination level in the system. Therefore, it is of paramount importance to address the issue of water losses in water distribution networks (WDNs). The issue with pump scheduling is to formulate an optimal policy that will allow water utilities to decide on the best strategy to minimize pumping costs for water distribution networks while providing an acceptable level of service to end users. Pressure control deals with monitoring and controlling the pressure at a node not to be too high (to reduce leaks) and also not to be too low (to meet the required pressure-head level needed to satisfy consumer demand at such node). In addition, water distribution networks are vulnerable to various sources of attacks that may be physical, cyber or a combination of both [5]. While numerous cyber-attacks on water distribution systems infrastructure have been reported [14–17], contamination of the water system due to chemical or biological means is also a challenge.

Another major issue affecting the operation of water supply systems for sustainable development is the increase in urbanization, which raises the water demand level. The human population in urban settlements is growing significantly. For instance, by 2025, most of the global population will reside in urban regions [18]. Furthermore, UNESCO [19] reports that by 2050, the human population in urban regions will increase from 3.9 to 6.3 billion. Of course, the rate at which urbanization increases will differ between countries. In Asia and Africa, an increasing population in the urban settlements in these regions is close to 90% [20]. This means that the people and industries in these regions will use a large portion of the total available water. The increasing trend in urbanization due to technology advancement cannot be overlooked. It poses a serious threat to the available water resources. Thus, if the current trend continues, then by the year 2030, water demand will tend to be more than the supply by 40% [21]. At this crucial stage, it then becomes necessary to revolutionize the water supply system for sustainable smart city development. The paper is organized as follows. Section 2 briefly discusses the need to improve water system operation, related studies and the main contribution of this paper. In Section 3, the revolutions taking place in the industrial and water sector are discussed while Section 4 presents the digital technologies needed to revolutionize water supply system operation. Section 5 discusses the potential application of the new industrial revolution in the water sector. In Section 6, the summary of the potential application of the digital technologies in improving the water system operation, the prospect of each technology as well as the technical challenges is presented while Section 7 concludes the paper and presents future works.

2. Motivation: The Need to Revolutionize the Water Supply System

Managing and monitoring large-scale water supply networks has been a serious challenge facing water utilities. In the past, monitoring and control capabilities in the water supply system are provided with supervisory control and data acquisition systems (SCADA). However, due to the dynamism, uncertainties and complexity involved in water supply system operations, there is a need to revolutionize the water industry with the current paradigm shift in technology to better monitoring and control capabilities. Hence, there is a need for in situ, smart systems for on-line monitoring of the complex water distribution piping networks. Unfortunately, the existing ICT solutions do not provide the capability to handle the dynamic nature of the water distribution networks. Thus, a renewed focus is aimed at the adoption of new digital technologies with such monitoring capability. The new industrial revolution termed "Industry 4.0" allows the use of emerging technologies with better monitoring and control capabilities, and better computational and decision support systems to optimize the operation of water supply systems. Thus, integrating SCADA with network simulation models and the features of Industry 4.0, proactive monitoring and control and management of the complex water supply distribution networks could be achieved. Such an integrated system forms the foundation of Water 4.0 for the provision of a real-time smart water network decision support system. To have a fully functioning system, the key drivers of Water 4.0 as well as the application domain where such an integrated system could be used in water supply systems are discussed. Furthermore, technical challenges and future opportunities offered by the technology for sustainable operation of municipal water services are highlighted.

Related Studies and Contributions

With the new industrial trend, the use of emerging digital technologies in the water sector is gradually becoming a reality. The initiative started a few years ago, when Sedlak [22] conceptualized the idea. The German water partnership has championed Water 4.0 initiatives since 2016. The concept of Water 4.0 is relatively new in the research community. Thus, only a very few papers on this subject matter are available in the literature. As of late, more studies are being conducted to assess the potential of these technologies in the water sector. Sedlak [22] was credited for the first insight into the subject matter. The author presented the problems with the water cycle and proposed the use of digital technologies to rescue degrading water facilities. Kijak [23] also discusses the potential of Water 4.0 in providing sustainable climate resilience. In [24], the relationships between 4.0s for industrial and other engineering processes that are focused on the organizational effectiveness were presented. A similar paper in [25] discussed a number of case studies reporting the application of digital technologies to minimize water losses. The author [26] discussed the problems with disinfection and corrosion control in the treatment plant, suggesting the need for Water 4.0. Alabi et al. [27] took a close look at the business side of Water 4.0 from the industry 4.0 perspective and developed an integrated business model for the water 4.0 revolution.

Based on our examination of the existing literature studies, we realized that no work has presented a comprehensive review and in-depth overview of Water 4.0 in the context of water supply system sustainability. To address this shortcoming, this paper presents a detailed overview of the trends and application of digital technologies for improving water supply network operation as well as research progress related to the use of each technology in the water domain. The key contributions of this paper are as follows:

1. This study presents an in-depth description of the key drivers of Water 4.0, and several tools and approaches used in each digital technologies of Water 4.0 as well as research trends;
2. Presentation of how the full potential of digital technologies could be harnessed for sustainable smart city development; thus, we cover different potential application domains of Water 4.0 in the water sustainability context;
3. A clear vision of the possible challenges of Water 4.0 during full scale implementation;
4. Introduction of some new research guidelines for future studies in this field.

To the best of our knowledge, this is the first article with such a review of Water 4.0 technology. The paper aims to contribute to a broader and deeper understanding of Water 4.0 and also motivates research scholars to become personally involved in an effort to improve water supply system operations through cutting edge research in the use of digital technologies for smart city development.

3. Moving from Industrial Revolution to Water System Revolution

Industry 4.0 is the fourth industrial revolution developed to meet multiple demands of additive manufacturing processes and has been implemented in multiple engineering fields such as provisioning of smart monitoring and control capabilities to water supply systems. A comprehensive study is taking place in this area. Figure 2 shows the four stages of the industrial and water system revolution. The industrial revolution can be traced back to its stem in manufacturing processes. It began with Industry 1.0, called the age of steam, involving the utilization of the energy from water and steam for production systems. Only a few products could be accomplished during this era, thus enhancing manufacturing activity led to the second industrial revolution called Industry 2.0. This revolution is also called the age of electricity where mass production with the use of electrical power was achieved. As illustrated in Figure 2, Industry 2.0 was revolutionized by the advent of information technology to automate production procedures. This led to Industry 3.0, which enhances process flexibility. More recently, studies and projects have been devoted to Industry 4.0, initially proposed in Germany [28]. This project is an initiative to revolutionize the manufacturing sector. This revolution consists of an integrated method for the use of emerging technologies which include cyber-physical systems (CPS), internet of things (IoT), cloud computing, artificial intelligence and automation to enhance productivity. This revolution offers a better way to use information, control, and communication theory to provide improved operations. The idea has been applied in some areas of engineering such as the medical field [29], smart logistics [30] and the energy sector [31,32]. As shown in Figure 2, the use of this concept is being proposed for the water sector. This is currently referred to as Water 4.0. Before the key drivers of Water 4.0 are addressed, an overview of the revolutions within the water system is presented. As shown in Figure 2, the first revolution in the water sector involved the use of local ad-hoc systems to pipe potable water in and sewage out of population centers. During the second stage, treating drinking water to kill infectious microbes and protecting users from diseases transmitted through the very success of Water 1.0 was accomplished through the use of large centralized infrastructure. Water 3.0 saw widespread adoption of computers and control in the water sector. One of the successes from such application is sewage treatment plants [33]. The current stage of revolutions in the water sector (Water 4.0) involves an integrated method for the use of emerging digital technologies, which include CPS, IoT, cloud computing, artificial intelligence, and automation to enhance water supply system operations.

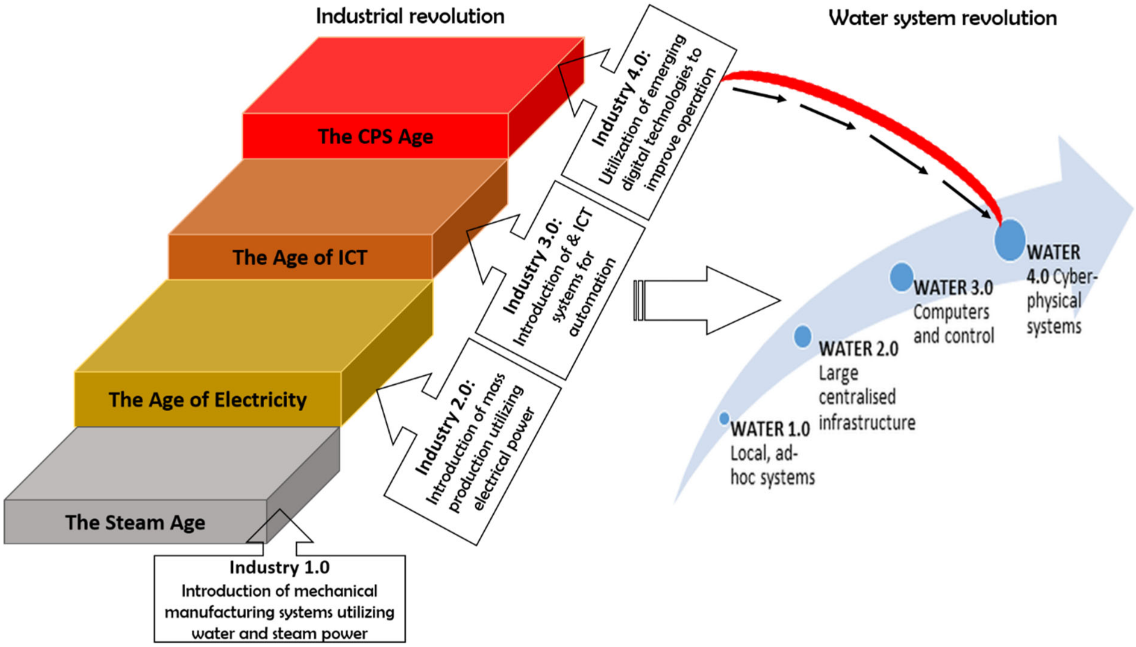

Figure 2. The four stages of the industrial and water supply system revolution.

Water 4.0 provides a unique opportunity to identify a promising approach to addressing future management problems in water supply networks. It incorporates the primary features of Industry 4.0 such as digitization and automation to achieve a systemic water management context. Through the use of automation and increased integration of sensors (for pressure, flow and temperature measurements) and model applications (such as the hydraulic model of water networks), opportunity may be created to better understand water management problems in terms of their complexity and to illustrate the use of Water 4.0 in production, early warning and for the decision making process. Water 4.0 also provides a greater ability to optimize the management of the water supply system to achieve efficient use of scarce water resources. Therefore, utilizing the key features of Water 4.0 in enhancing water supply network management operations motivates the need to conduct more research in this area. However, in addressing this, the salient features of Water 4.0 need additional study. These include digitization which entails the IoT and internet of services, big data analysis, CPS, and automation, amongst others. For real-time control processes, the IoT and internet of services are crucial. It is necessary to investigate how Water 4.0 could be utilized to meet the requirements of the complex water supply systems.

4. Digital Technologies in the Water System: Key Drivers of Water 4.0

Today, through the introduction of the IoT and CPS, the worlds of manufacturing and network connectivity are incorporated to make Industry 4.0 a reality [27]. The emerging digital technologies used in this concept are shown in Figure 3. These technologies are briefly discussed in the next sections.

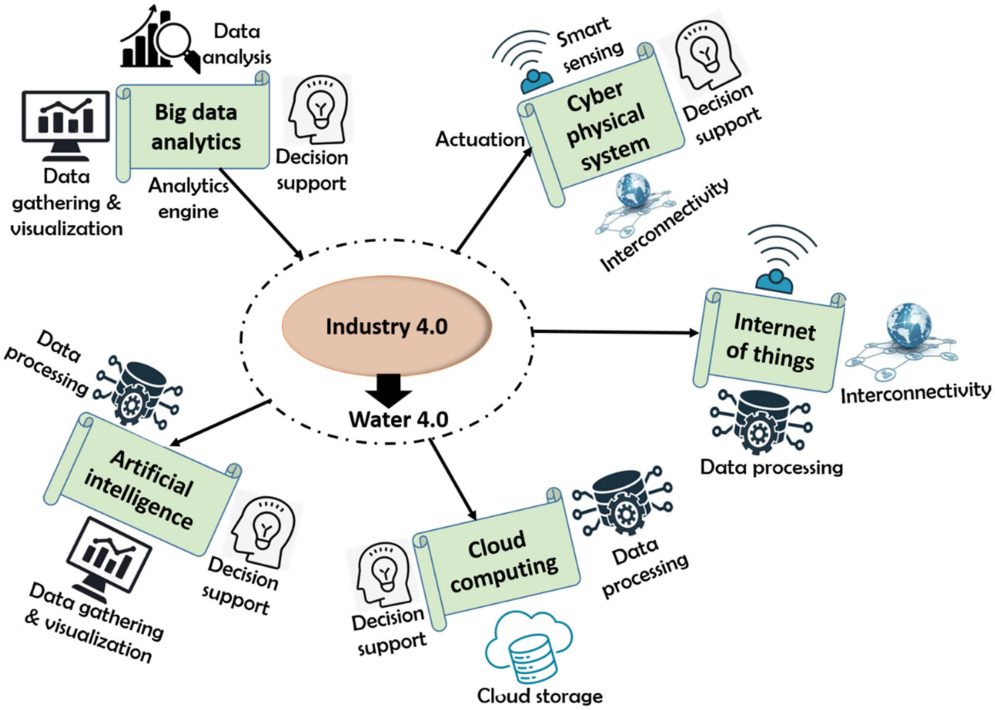

Figure 3. Emerging digital technologies used in water 4.0.

4.1. Cyber Physical System

The CPS is the basis of Industry 4.0 [34–36]. CPSs are a fusion of networks, computation, and physical environment in which embedded computing devices continuously sense, monitor, and control the physical environment [37]. CPS represents one of the most important accomplishments in the development of ICT [38]. A simple view of a cyber-physical system (CPS) architecture is illustrated in Figure 4. The physical process is the environment to be monitored or controlled using sensors and actuators. The acquired information from the physical process is sent to the cyber systems (where decisions are made) through a communication network [16,39].

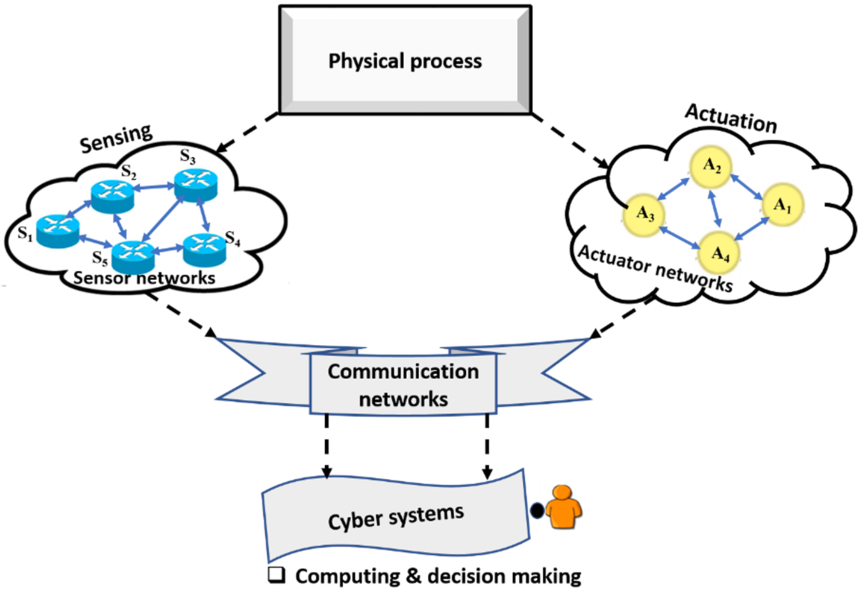

Figure 4. A simple view of CPS architecture [16].

In Water 4.0, the physical process of the CPS could be the whole water supply system or a section in the operation of the system such as monitoring water quality at the water treatment station, monitoring water quality and leakage flows along the distribution networks, or monitoring energy consumption due to pumping at the pumping stations. In this context, different sensors and actuator mechanisms such as pressure, flow, water quality, accelerator sensors and control valves are deployed for real-time measurement and control of the physical environment. Thus, through sensor and control valve integration, the provision of real-time monitoring of water quality along the complex distribution network could be achieved. Research studies in [40] have shown that machines/systems can interact with one another and decentralized control systems to improve manufacturing through the implementation of the CPS. The CPS is closely similar to other emerging research topics such as the IoT, machine-to-machine (M2M) systems, and ubiquitous, fog and pervasive computing but with better control capabilities. They are sometimes used interchangeably to mean a similar idea.

Some essential components of a CPS are sensors and actuators. While sensors are used to gather information about the condition of the water system, actuators are used to act on the data by carrying out particular tasks according to the application. pH sensors, dissolved oxygen concentration (DOC) sensors, flow rate sensors, and turbidity sensors are the most commonly used sensors for water quality and anomaly detection. In view of this, Table 1 [41] presents targeted water quality parameters with widely acceptable ranges for potable water. These values are tracked continuously to ensure that water quality is not compromised. The DOC is a frequently monitored parameter that is used to access the pollutant level in a water system. Since a minor decrease in the DOC represents potentially fatal results [42], accurate and real-time data are frequently the most favorable. In some cases, due to environmental concern, DOC sensing can be obscured; therefore, having robust training data using the water quality parameters will improve the effectiveness of the system. For leak detection purpose, pressure, flow rate, acoustic, ultrasonic and temperature sensors are frequently used. A combination of one or more of these sensors has been employed for leak detection purpose. The temperature sensor provides continuous measurements of the outside temperature within the pipe environment and these data are used to create a baseline. It is a general belief that a leak flow via an orifice in a pipe creates a local temperature anomaly. Each temperature measurement is then compared to the baseline and a deviation from the baseline indicates the presence of a leak.

The actuators used in CPS, for example, in a water quality application, perform actions such as regulating the opening and closing of the isolation valve to segregate the pipe whose water quality is compromised from the network or to halt the flow of water in such pipe. In a leakage detection application, in the event of leaks, the actuators react by overseeing the control of the pressure-reducing valves to lower the pressures at the nodes of the leaky pipes.

Table 1. Some water quality parameters and acceptable ranges.

Parameter	Acceptable Range for Potable Water	Unit
pH	6.5–8.5	pH
DOC	>3	Mg/L
Electrical Conductivity	500–1000	µS/cm
Temperature	5–30	°C

The sensor reading is sent to a remote processing area for real-time water quality analysis via wireless communication technology. The wireless communication technology used ranges from short to long range, and high to low power. Amongst the low-power wireless communications, SigFox is power efficient and has the potential to cover relatively large areas in rural settings (up to 50 km). However, the rate at which these data are transmitted is relatively low. Similar to SigFox in data transmission rate, LoRaWAN is another long-range low-power wireless communication system that can be employed due to its potential to cover up to 20 km in rural areas [17]. Additionally, 3G/LTE and LTE-A offer reasonably fast data rates over long distances of up to 30 km, but when compared to other wireless communication technologies, their power utilization is rather high. The literature [43–46] contains research papers on wireless communication technology utilized for this purpose. For the Water 4.0 architecture to monitor the water supply system infrastructure, long-distance communications with a relatively good data rate are required. Currently, short-range communications are used in CPS architecture. However, future CPSs should take into account incorporating the long-range wireless communication technologies into the system to improve communication coverage in order to provide dependable monitoring of water distribution networks, which are large-scale.

Practical applications of CPSs for the management of water systems have been reported in the literature [47–49]. The research study in [47] presents a CPS framework for real-time control of the urban water cycle as illustrated in Figure 5. In this study, water hydraulic and quality conditions are monitored in real-time. Hydrodynamic modelling is integrated with real-time measurements to generate quality and hydraulic models for optimal control and diagnosis.

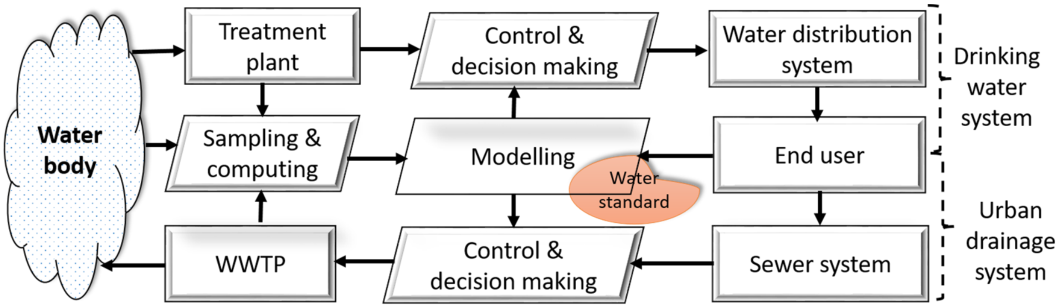

Figure 5. A CPS for the control of urban water cycle [47].

Nasir and Song [50] proposed a CPS architecture for in-pipe water quality monitoring. The proposed system illustrated in Figure 6 is similar to the conventional wireless sensor network. The physical layer is the water distribution system to be monitored for water quality application. In this context, data from water flow, pH, and contamination sensors located in the sensing platform are acquired, transmitted, processed, and analyzed at the network layer. The data are managed effectively and stored in a database management system. The application tier includes various services for the system administration and a normal user. Lambrou et al. [51] developed low-cost real-time monitoring and contaminant detection in a drinking water distribution system. In [52], a mobile sensor system is utilized to map river water quality based on in situ data collected in a few Indian rivers. The data visualization generated permits the detection of pollutant sources. The proposed system has been used to monitor and regulate quality of large bodies of water. The authors in [41] presented a soft computing framework using a multi-sensor array for water quality monitoring. Several other applications could be found in literature to show the potential of CPSs for the provision of sustainable water systems [53–55].

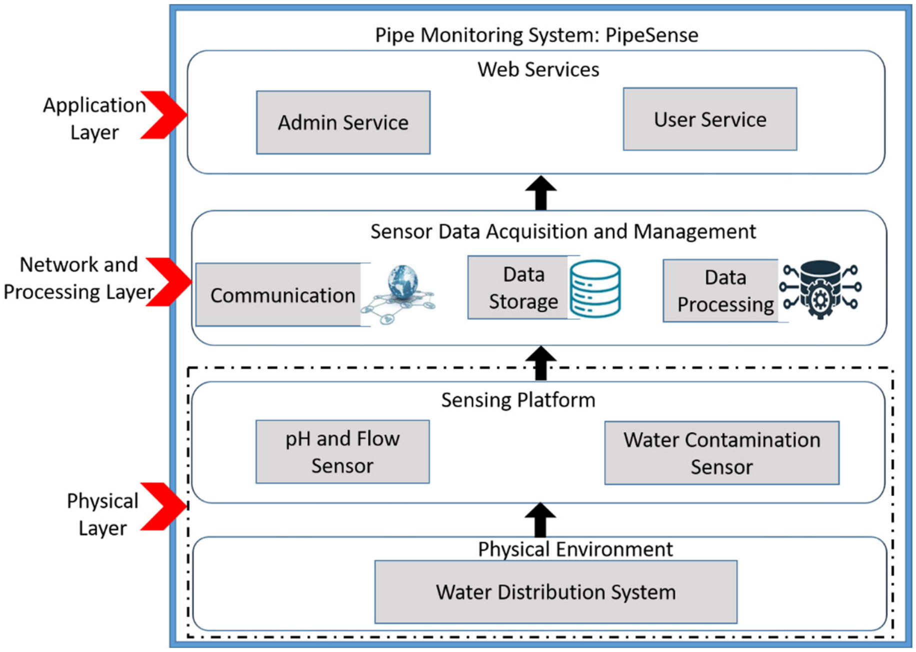

Figure 6. Architectural framework for in-pipe water monitoring system [50].

4.2. Internet of Things

The IoT has enjoyed a tremendous development in the industrial sector for revolutionizing the existing manufacturing systems and was regarded as a key technology for the next generation of manufacturing systems [27,34,56]. Most notably, IoT has aided smart factories [57]. This enables factory managers to automatically gather and analyze data in order to make better decisions and optimize production. The data from sensors and machines are communicated to the cloud by IoT connectivity solutions implemented at the factory level. It is possible to apply the same technology to water supply systems. At present, the operation of WSSs is controlled with the use of SCADA systems. In Water 4.0, IoT is anticipated to provide good transformative alternatives to improve the operation of many industrial technologies such as SCADA. IoT connects the internet and the smart water networks sensing devices and gathers useful data regarding the state of water distribution networks to assist in controlling, treating, and decision making. IoT through its smart sensors and devices provides real-time continuous monitoring capabilities to complex water piping networks. Leak flow, water flow, water level, and pressure along the distribution network can be monitored effectively in real-time with the help of IoT. Moreover, the provision of real-time monitoring of water quality along the complex distribution network could be achieved. This is one of the initiatives of smart water network management.

Several countries have keyed into smart water network initiatives. For instance, Singapore, South Korea and Malta have regulatory policies where it has mandated the use of digital technologies to improve smart water grids and to reduce utilities' water loss to less than 12%. Recently, smart metering, which involves the deployment of automatic meter reading (AMR) and advanced meter infrastructure (AMI), is another application of digital technology in the water sector. AMI networks are used for accurate metering and billing. These devices have the capacity to improve the accuracy of usage-based data for billing and also reduce cost from leaking pipes. Nowadays, several water utilities and municipalities are investing in AMI. In South Africa, a MICROmega Group Company launched a utili*Meter*, which is an AMI-enabled water management device [58] coupled to a traditional water meter to provide a standard transfer specification-approved smart prepaid water metering solution. This technology allows rapid response to leaks and tampering, along with prepaid, post-paid, flat rate, and flow limitation water metering. In South Korea, Gochang Water Works implemented smart water meters in 24,000 households at the end of 2017. Examples of such smart water systems with AMR technology are LoRa AMR system water meters (see Figure 7). These can achieve water supply control through real-time communication and active data transmission. They adopt full package sealing technology to achieve Ip68 protection. The features of these meters are provided in Table 2 [59]. In the middle of 2019, South East Water announced trials in partnership with industrial experts to develop and connect smart water meters and place acoustic sensors along underground pipelines using Vodafone's Narrowband-IoT (NB-IoT) [58]. Thus, the use of IoT in the water sector is increasingly gaining momentum.

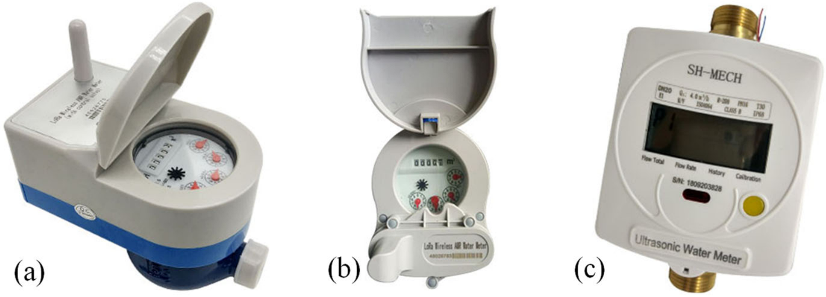

Figure 7. Samples of AMR water meters with LoRa communication technology (**a**) LoRa remote water meter; (**b**) electronic remote valve control water meter; (**c**) wireless ultrasonic LoRa water meter [59].

Table 2. LoRa AMR water meters' specifications.

LoRa Water Meter Class	LoRa Remote Water Meter	LoRa Electronic Remote Valve Control	Wireless Ultrasonic LoRa Water Meter
Size	DN15-DN20	DN15-DN25	DN15-DN40
Materials	Iron	Brass	Brass pipe
Type	Liquid sealed	Dry-dial	Dry-dial
Standard	ISO4064 class B	ISO4064 class B	ISO4064 class B
Temperature Class	T30	T30	T50
Max. Pressure	1.0 MPa	1.0 MPa	1.6 MPa
Battery Life	6 years	6 years	6 years
Meter Reading Frequency	1 day/time	1 day/time	1 day/time
Communication Method	Lora	Lora	Lora

4.3. Big Data Analytics

In water supply systems, as water utilities deploy smart meters, sensors, and other IoT hardware, water utilities will inevitably handle an enormous amount of data relevant to its operations. Big data (BD) is a term used to describe collections of massive datasets with a large amount of diversity that are challenging to analyze using traditional tools and methodologies [60–62]. These data are different from the traditional large dataset owing to some features regarded as the 4Vs of BD, which are volume, velocity, variety, and veracity. The volume indicates the amount of the enormous data generated. Datasets in the range of exabytes have been regarded as BD [63]. Of course, this is not constant and solely depends on the time, data types, and application type [64]. The velocity features of the BD concern the speed at which the data are generated and the rate of analysis. The BD whose volume increases rapidly over time, could be generated in real-time/near real-time, batches, streams or bits. The variety refers to the nature of the data. This could be structured, semi-structured or unstructured. Structured data are those that are well-organized and can be easily stored in relational databases, and categorized and referenced in tabular form, which makes them easily readable by machines [65]. Data obtained from WDN are categorized under unstructured data. Unlike structured data, text, video, and other multimedia content are unstructured because they are random and lack structural organization, which makes them difficult to analyse. The last feature of BD is veracity, which concerns security and indicates untrusted and uncleansed.

IoT intelligent sensors generate data related to pressure and flow profiles along each pipe of the complex piping networks. These data require an intelligent analytical solution to be used efficiently for particular applications. For instance, the data from smart acoustic sensors, vibration sensors and accelerometers can be interpreted for leakage analysis applications. In some cases, the data from pressure sensors installed at several points along the piping networks could be used for leak interpretation and generation of leak alarms. Hence, proper interpretation requires a good analysis of such data. The application of advanced analytical techniques to leverage large volumes of heterogeneous data to obtain useful information is generally referred to as Big Data analytics [65]. One area of application where big data analytics may be useful is in the support of sustainable groundwater management and water treatment facilities [66,67]. As previously mentioned, IoT systems generate a huge amount of data from the connected smart devices and sensors, and the applications which have to be managed efficiently [68]. The large data are stored in the meter data management platform. This platform is desired to manage large data from the installed millions of devices involved in the connection. Several data analytical tools such as Apache Hadoop and Apache Spark may be employed to analyze the data for decision making. In recent times, machine learning, data mining, and computational intelligence algorithms [63,69] have proven their accuracy and scalability in providing analytical solutions to BD. The South East water utilities is implementing Xylem's Visenti for Software analytics to manage and analyze sensor data installed on water system infrastructure. Smart meter data produce accurate insights on the end user's water consumption pattern, and improve accuracy of demand- and supply-side forecasts. The analysis of data from a smart meter could also provide relevant critical insights into what might happen to the infrastructure in terms of future prediction of pipe failure.

The potential of BD analytics in the water sector has been the subject of several research projects. Ai and Yue [70] present a framework for processing and analyzing big data related to water resources for use in real-time applications. The use of big data analytics in the water, sanitation, and hygiene sector was proposed by [71]. Investigation shows that it is possible to effectively monitor system data performance and post implementation for sustainability. Chalh et al. [72] present big data open platform architecture which helps to provide an effective tool that permits water utility managers to solve water resource and water modelling challenges. The platform could also be used to aid decision making. With the inclusion of a geographic information system, database management, data analytics and communication, and a knowledge-based expert system, the water utility manager can compare the effect of different current and future management scenarios and make choices to preserve the environment and water resources. In [73], a framework and prototype for big data analytics-based water resource sustainability evaluation was proposed. Results obtained show that the proposed prototype can be used to evaluate regional water resource sustainability and environmental performance in practice and provide scientific basis and guidance to formulate water supply policies. Research studies on leveraging big data analytics for the management of water resources can be found in [74–77]. Hence, in Water 4.0, smart analytics solutions are required to improve overall system performance. Once the necessary data are obtained from water utility facilities, good analytics and decision frameworks may pilot water utilities to a well-optimized efficiency.

4.4. Artificial Intelligence (AI)

In recent years, machine learning, which is a subset of AI, has gained momentum in the water sector. Artificial intelligence involves the simulation by machines, particularly computers, of human intelligence processes such as learning, reasoning, and self-correction. It is an essential technology which, with the help of the computer, is programmed and controlled by machines [29]. Some of the potentials of AI in the water sector are shown in Figure 8.

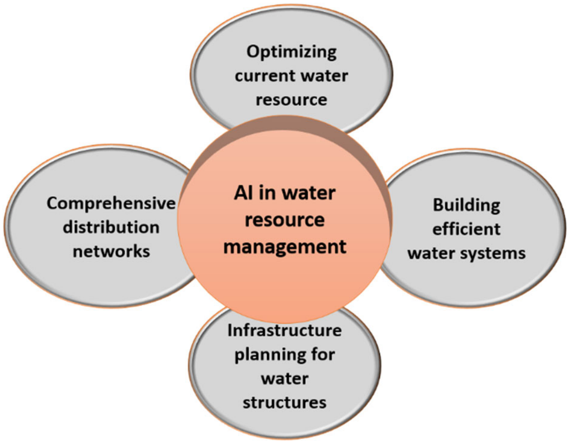

Figure 8. Some of the potentials of AI in the water industry.

The optimization of current water resources can be achieved with the decision-making abilities of AI, where decision support systems [78–81] are used. Another key potential of AI in the water sector is infrastructure planning. Water utilities can employ AI-driven planning to gain a better understanding of real-time water loss and usage, allowing them to build and implement a comprehensive and adaptive distribution network, as well as provide revenue for financial activities. Several studies have reported the use of AI for demand forecasts [82–85], which set pace for future planning and expansion of infrastructure. In water supply systems, a human decision such as water quality awareness, shutting down pipes whose water quality has been compromised, etc., could be made by AI. In some cases, AI could be used to analyze complex water network data. For example, the data from a ground penetration radar used for leak localization can be analyzed. Machine learning approaches are the first step in AI-based frameworks. Several machine learning methodologies have been deployed to the water industry [86–88]. One such application is the estimation of the likelihood of event occurrence and the raising of corresponding alarms using Bayesian networks [87]. Elsewhere [86], advanced AI, machine learning, and statistical methods are used to established risk of pipe burst. One of the promising applications of AI in water supply networks is the provision of on-line monitoring through the development of robotic systems for in-pipe monitoring [89]. This system monitors the pipe for fractures, cracks, and areas of leak occurrence. The use of AI for water quality prediction has been reported in the literature [90–93]. In this application, the water quality index (WQI) and water quality classification (WQC) may be achieved as illustrated in Figure 9.

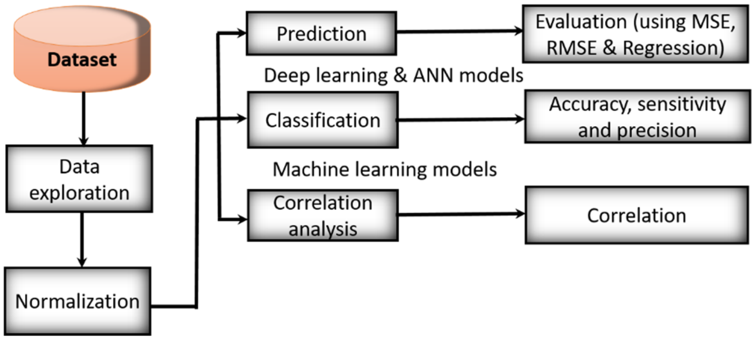

Figure 9. A framework for the application of AI for water quality monitoring [90].

In Aldhyani et al. [90], an AI algorithm was developed for the prediction and classification of water quality. For the WQI prediction, a nonlinear autoregressive neural network (NARNET) and a long short-term memory (LSTM) deep learning algorithm were used. For the classification, support vector machine (SVM), K-nearest neighbour (K-NN), and naive Bayes were utilized. Prediction results demonstrated that the NARNET model performed slightly better than the LSTM for the prediction of the WQI values, and the SVM algorithm achieved the accuracy of 97.01% for the WQC prediction. Furthermore, the NARNET and LSTM models achieved similar accuracy in the testing phase with a slight difference in the regression coefficient. Because the AI technique employs early warning indications that allow for the detection of extreme events on a water distribution system [94], combining it with cutting-edge control devices allows for quick intervention and a reduction in the risk of contamination. Ahmed et al. [95] proposed an artificial intelligence framework for improving water resource management. The proposed system makes use of data from a multisensory array that includes flow sensors, pH sensors, water pressure valves and ultrasound sensors. The experimental results show that the intelligent system permits the analysis of water quality with a root mean square value of 15.12%, and reliability of 98.24%. Fan et al. [96] proposed a clustering and semi-supervised learning AI framework for leak detection and localization in water distribution networks. The framework advances the leak detection strategy by alleviating the data requirements, guiding optimal sensor placement, and locating leakage via WDN leak zone partitions. The proposed system is scalable and its applicability to various WDNs prove its potential for sustainable management of WDNs with 95% detection accuracy. The studies conducted in [97] present a machine learning approach that helps to identify leak locations based on pressure sensor measurements. A random forest classifier is used for small-sized and medium-sized benchmark networks. The presented results show that the proposed methodology can be successfully used for leak localization using data obtained from numerical simulations even for sparse sensor placement. The authors in [98] use expert knowledge and data-driven models for leak detection and localization in WDNs. Analysis performed on a Barcelona WDN dataset with both real and simulated leaks showed that the proposed solution can improve the leak detection and localization. In Xiang et al. [99], an adaptive intelligent dynamic technique was developed for water resource planning. A computational intelligent system was proposed by [100] for leak localization in WDNs. The effectiveness of the proposed system was demonstrated on Modena WDN data, and the results obtained show that the proposed intelligent system gives a satisfactory performance in terms of leak detection, leak size estimation, and localization.

By leveraging on digital tools for automation of water network management operations, a long-term holistic vision of an integrated water network management could be created. This will act as a central system of record and control of water assets. Thus, AI is one of the emerging technologies needed in Water 4.0 to enhance the operational management of water supply systems. Several efforts are ongoing to build algorithms with smart sensors and artificial neural networks that will dynamically strategize water operations more intelligently. Prediction models for future water demand, robotic sensors in water systems, and block chain technologies to cater for financial transactions related to meter billing are feasible with appropriate application of AI techniques.

4.5. Cloud Computing

Cloud computing is one of the new computing paradigms which permit the provisioning of a reliable and quality of service-guaranteed dynamic computing environment for end users [101]. Cloud-based computing technologies can make a significant contribution to Water 4.0 realization. Cloud computing has powerful storage, processing and service ability [102]. When combined with the IoT's capability of information collection, utilities can have access to scalable, on-demand services that are provided through web-based technologies. In Water 4.0, cloud computing is expected to share resources such as water piping network data to achieve coherence and economies of scale. As discussed in the previous sections, water supply systems generate a huge amount of big data from its components such as the information from water distribution networks, water treatment stations, and pumping stations. A huge volume of this data could be sent to a cloud computing center for processing, computation and storage, which eases monitoring operations of water supply systems. Most of the AI training and inferences are performed in the cloud and as a result of the cloud network's scalability and flexibility, many organizations have chosen to rely on cloud computing, storage, and networking architecture.

Table 3 gives the summary of the features and potential application domains of the key drivers of Water 4.0 in the water sector. The CPS has been widely used for water quality monitoring where sensor technologies were utilized to acquire a huge amount of data to capture changes in water quality parameters along a pipe network. This is usually achieved through sensing, communication (through wireless system), and control (using actuator networks). Similar to the CPS, the IoT has been widely used for leak detection and monitoring, water quality detection, and pipe health monitoring, among others, although the CPS offers better control capabilities [16]. Currently, research studies focus on the use of AI in the water domain. It requires gathering necessary data related to the utility facility, analyzing the data and making optimal decisions using a decision support system. In this, both supervised and unsupervised machine learning algorithms are employed. Among others, anomaly detection and water demand forecasting are the most famous applications of AI in the water sector. Nevertheless, its utilization for pipe health monitoring as well as water quality detection in water treatment stations cannot be overlooked. Among these digital technologies, cloud computing is seldom used in the water sector. It encompasses data processing, storage, and decision support and has found applications in the management of water resources and water quality detection. Because the CPS and IoT require deployment of numerous sensing and/or actuating devices relevant to the specific application, the success rate of such systems depends on the robustness of the sensing and communication devices used. For instance, in a water distribution network application where the sensors are exposed to severe temperatures and harsh environments, the long-term durability of the sensing device is a challenge.

Table 3. Comparison of the key drivers of Water 4.0.

Digital Technology	Features	Applications	Application Rate	Success Rate
CPS	Sensing, communication and control (through actuators), decision system	Water quality detection (WQD) [103–105], leak detection [106], pressure control and monitoring (PCM) [107], state estimation and monitoring (SEM) [108,109], demand prediction and monitoring (DPM) [110], pipe health monitoring (PHM) [111], water resource management (WRM) [112]	Mostly employed	Success rate depends on the sensing and communication devices used.
IoT	Smart sensing, data processing and communication	Leak detection [113,114], WQD [115], PHM [116,117], pressure monitoring [118], WRM [119]	Most employed	Success rate depends on the sensing and communication devices used.
BD Analytics	Smart sensing, data analysis and decision making	Leak detection [120], WRM [121,122]	Less employed	Success rate depends on the quality of the data and complexity of the analytical algorithms.
AI	Data gathering, data analysis, decision support system	Anomaly detection [123,124], PHM [125,126], DPM [127,128], process automation for water treatment and desalination [129,130]	Less employed: Current application focus	Success rate depends on the quality of the data and machine learning algorithm used.
Cloud Computing	Data processing, storage and decision support systems.	WRM [131,132], WQD [133,134].	Seldom used	Success rate depends on the quality of the data and complexity of the analytical tools.

Deploying smart sensors to gather water quality data from a water pipe network installed in a harsh underground environment is a big challenge. This is because flora aggregate [135] may be found around the sensors, which depletes the sensing power and the operational performance of the sensing device. This may affect the quality of the acquired data needed for other digital technologies (AI, BD analytics, and cloud computing). Therefore, the success rate of AI, BD analytics and cloud computing will depend on the quality of the data and complexity of the algorithms used for data analysis. In addition, complex water network analysis could be performed using hydraulic models to gather sufficient water quality or leak data needed for AI and BD applications. Research studies in this domain can be found in [136,137].

5. Potential Applications of Water 4.0

The emerging technologies used in Water 4.0 have allowed its adoption in the water system applications domain. As illustrated in Figure 10, these applications include water quality monitoring (WQM) along the distribution networks, leakage detection and monitoring (LDM), PCM, and PHM. This applications domain is perceived as a long-term challenge common to most water supply systems.

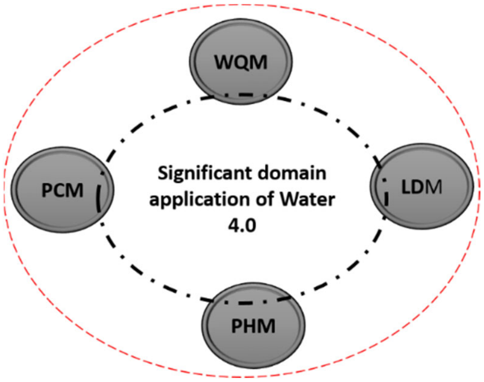

Figure 10. Water 4.0 significant water supply system application domain.

5.1. Pipeline Health Monitoring

A major component of a water distribution network are pipelines for potable water delivery to end users that have been placed underground for several years. Due to ageing, or third-party intervention, damages occur to these structures which causes waste of a significant amount of water. Before that, a fracture may occur on the pipe surface due to vibrations of the surrounding environment or corrosion. Several causes of pipeline damages may be found in the literature [138,139]. Due to the significance of these damages, the monitoring of the health status of pipes before deformations occur is crucial. This could help in reducing losses if active intervention takes place once a particular section of the pipes in the network is found close to deformation. Pipeline health monitoring involves monitoring of pipes for corrosion, deformation, and vibration, as well as leaks. In the past, several methodologies were used to monitor pipelines which range from the deployment of wireless sensor networks [140] to the use of accelerometers and soft capacitive sensors [141]. When deformation is detected, active control mechanisms and decision support systems are required to relay the problems in real-time. In recent years, with technology improvement, Water 4.0 could provide capabilities to report areas of deformation as well as active control mechanisms and decision support systems to help utilities improve on the previous system operations. A typical example is the use of smart robotics for pipe health monitoring [142]. Furthermore, edge AI has the potential to create automated closed-loop systems that continuously monitor the health of critical infrastructure. Thus, the sustainable operation of the water supply system is guaranteed.

5.2. Pressure Control and Monitoring

In water distribution networks, pressure sensors are mounted at nodes of the network to measure water pressures along the pipes and at each node. Pressure and water demand share a good relationship. When the demand increases, more pressure must be applied to a node to meet the increasing demand. Thus, for the satisfactory supply of potable water to the end users, service pressure must be sufficient to adequately satisfy demand at the node. Unfortunately, when considering leaks, the reverse is the case to reduce the level of losses in the system. The issue is therefore more complicated than originally assumed. More so, consumer demand is not linear, which makes pressure control a difficult task when dealing with leak reduction. Therefore, demand uncertainty is another issue affecting the accomplishment of good pressure control in systems. With the advent of new technologies, if the pressure and demand at a given node can be monitored in real-time through the integration of pressure and flow sensors, an active control system for pressure control at nodes having the leaking pipes could be achieved. This is one of the features of Water 4.0. Thus, with CPS and IoT as well as the advanced control and actuator mechanism offered by this technology, optimal pressure control in real-time may be accomplished.

5.3. Water Quality Monitoring

In water quality applications, the deployment of integrated sensing devices is required to provide continuous real-time measurement of data related to pH, temperature, turbidity, dissolved oxygen concentration, and chlorine residual level along the distribution networks. With the help of the CPS features of Water 4.0, which are integrated with control valves and active decision support systems, an optimal decision regarding the state of the water in the distribution piping networks could be achieved. For instance, in a situation where contaminants are detected and quality is compromised, active decision making is required for immediate action to be taken on water contamination before it spreads to the entire system. In most cases, necessary actions include the closing of valves at the particular node where the pipe conveying the contaminated water is attached. The valves installed at the entrance of a DMA of the water distribution network could also be controlled to stop the spread of contaminants.

5.4. Leakage Detection and Monitoring

This is also similar to water quality monitoring applications. In this system, an integrated number of sensors such as pressure, vibration, acoustic, and flow sensors and actuators are deployed for measurement and control activities. In [143], an in-pipe system is developed for pipeline leak monitoring. Furthermore, several research studies have reported the use of machine learning (a division of AI) for leak detection purposes [144–146]. Once a leak is detected and localized, monitoring of the leaky pipe is required for active intervention and repair and to avoid future leak occurrence in such a pipe. Thus, Water 4.0 could be used to provide real-time continuous monitoring to such a system.

6. Summary, Prospects, and Challenges

In recent years, we have been on the verge of a new industrial revolution in which emerging digital technologies and ICT are utilized in industries to improve operations through seamless control and monitoring of operational stages. Digital technologies have a good prospect to enhance the operation of water supply systems for sustainable development and are currently being applied in the water sector. For instance, in the use of digital technology for monitoring water quality level on a global scale, the water utility monitoring market has a growth of more than 5.11% CAGR during the period of 2018 to 2022 [147]. With the increasing use of ICT, data for the relevant water process becomes increasingly feasible and may be analyzed using big data analysis. Therefore, further analysis could be performed with other data such as weather to generate a water demand forecast for future planning and decision making. The IoT, AI, and other emerging digital technologies have the potential to transform the water sector by improving day-to-day water management and addressing long-term challenges of water leakage [148].

A digital transformation of a water supply system for sustainable development is shown in Figure 11. In this figure, an IoT-based smart water network management (SWNM) application is illustrated to achieve real-time continuous measurement which relates to the state of the network. The data must be continuously acquired, processed, and transmitted via wireless means to a remote center where further analysis takes place for optimal decision making. Most modern smart sensing devices possess in-built data storage and processing capabilities, which makes it possible to pre-process the data within the network [2,3].

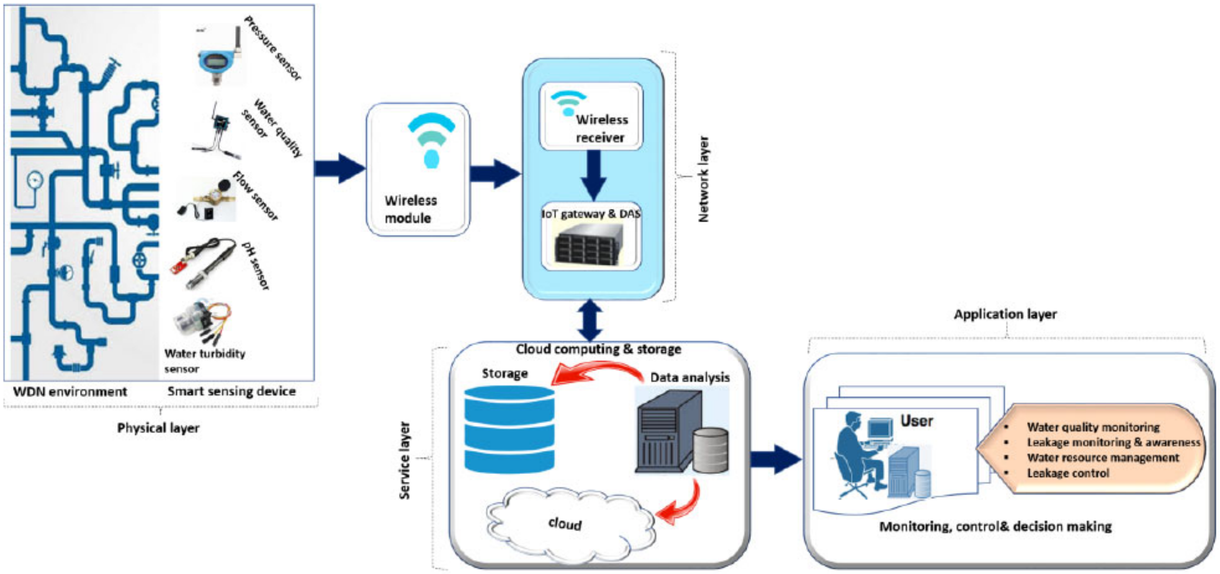

Figure 11. SWNM application framework [149].

The market size of IoT in utilities is estimated at $28.6 billion in 2019 and is expected to reach almost twice that amount (that is, 53.8 billion) by 2024. This corresponds to a compound annual growth rate (CAGR) of 13.5%. It has been proved that utilities with IoT features will be able to eliminate operational inefficiencies, optimize resources utilization, and increase the reach of service to more end users [150]. While the IoT has uplifted the utilities segment of oil and gas and the energy sector, the advent of this technology is now clearly visible in water utilities.

Monitoring the complex water supply distribution network in real-time is a challenging task. Nevertheless, Water 4.0 is conceived as a revolutionary methodology for improving operational performance and providing water distribution networks with monitoring capabilities. Thus, the overall picture of such an idea is promising. Information and communication technologies (a feature of the Water 4.0) can play a crucial role in solving the various challenges associated with water distribution network management. ICT-based systems can be used to safeguard water distribution networks, prevent unauthorized physical access to susceptible or vulnerable regions, and provide security surveillance systems. However, the security flaws within wireless systems result in security risks to WSS infrastructure monitoring [151]. In Water 4.0, the CPS and IoT smart sensing devices communicate via wireless communication technologies to enhance the system's flexibility, but due to the broadcast nature of wireless media, they pose more security risks [152] and are susceptible to multiple cyber-physical attacks. A successful attack on WSS could cause various levels of damage such as long operational downtime and economic loss to utilities. This makes security a critical factor to consider before large scale deployment of these digital technologies into water supply systems. Therefore, cyber-security is a serious issue in ICT-based water management systems. One of the most perilous threats in the internet is Denial of Service (DoS) attacks [153–155] where the resources of a system are exhausted until the system fails to provide its usual services in a timely fashion. Some more severe types of DoS are Distributed DoS (DDoS) and advanced persistence DoS (APDoS) where a large number of hosts simultaneously attack a victim site [155]. The APDoS can be intended to permanently destroy data or computing resources. It has been reported that there were more than 3 million active DoS attacks per month in 2016 and these attacks are expected to exceed 17 million by 2022 [155]. Nevertheless, once the source of the attack is determined, it is easy to defend the system by blocking the traffic coming from the attacking site.

In modern times, advances in sensor networks, CPS, and the ubiquity of the IoT have tremendously increased the acquisition of enormous amounts of data related to the application environment. Unfortunately, due to noise and other environmental factors, the data collected from sensors are inherently uncertain, incomplete and inconsistent. Uncertainty can also manifest when converting between different data types or when analyzing data of mixed types [156]. Each feature of BD introduces numerous sources of uncertainty. As the volume, variety and speed of the data increases, the uncertainty that inherently resides also increases. Mitigating uncertainty in BD analytics should be at the forefront of any AI techniques as uncertainty can significantly affect their performance. More studies are required to model and represent uncertainties that result from BD and analytical solutions. Since computational intelligence algorithms have been utilized to tackle uncertainties with some level of success [157–161], developing some computational intelligence metaheuristic algorithms for mitigating uncertainties that inherently reside in big data analytics is essential. Thus, more research studies are required in this regard.

Furthermore, continuous and autonomous monitoring of water supply system infrastructures requires a constant power supply for the CPS or IoT sensing and communication devices. In severe applications such as monitoring water quality and leaks in underwater or underground pipes, enhanced battery life and optimal energy usage are highly essential. Therefore, there are still many challenges that need to be tackled to guarantee a smooth transition.

7. Conclusions

Digital transformation of the water system for sustainable water supply is a necessity owing to the dynamic nature of water systems and consumer demand uncertainties, among others. Digital technologies have the potential to transform the operation of water systems by improving day-to-day water management and addressing long-term challenges and water security. With increasing use of ICT, data for the relevant water process become increasingly feasible and may be analyzed using big data analysis. Therefore, further analysis could be performed with other data such as weather to generate a water demand forecast for future planning and decision making. Therefore, Water 4.0 is seen as a revolutionary methodology for improving operational performance and provide real-time monitoring capabilities to complex water distribution networks. As water utilities embrace the IoT, it is important to develop a roadmap for digitalization. In this paper, an overview of a Water 4.0 framework that seeks to enhance the management and operations of water supply systems was presented. The basic features and emerging technologies used in Water 4.0 were discussed. In addition, challenges and the prospects of the new industrial revolution in the water sector were discussed. Although digital technologies are being deployed in different sub-sectors of water systems, so far, a full-scale implementation has not been reported in practice. In general, many challenges still need to be addressed to guarantee a smooth transition. Security, data quality and uncertainties as well as energy solutions for smart sensing devices are some of the biggest challenges to be addressed in order to harness the full potential of digital technologies for sustainable smart city development.

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