Digital Technologies in the Water System

Subjects: Engineering, Electrical & Electronic

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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. With the increasing growth in technology, the water sector is moving to the full phase of digitalization to enhance the sustainability of systems.

AI | cyber physical system | ICT | Industry 4.0 | Internet of Things | Water 4.0 | water loss

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

Today, through the introduction of the internet of things (IoT) and cyber-physical systems (CPS), the worlds of manufacturing and network connectivity are incorporated to make Industry 4.0 a reality [1]. The emerging digital technologies used in this concept are shown in **Figure 1**. These technologies are briefly discussed in the next sections.

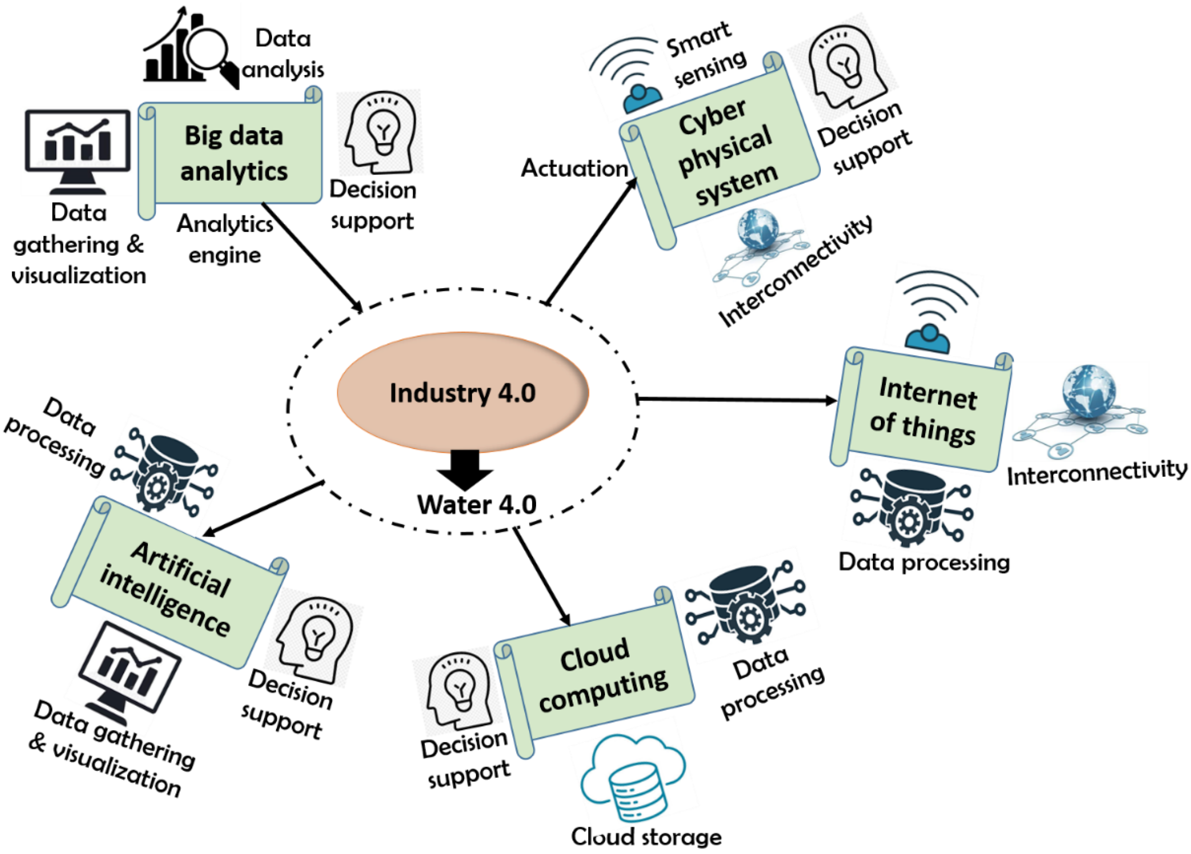

Figure 1. Emerging digital technologies used in water 4.0.

2. Cyber Physical System

The CPS is the basis of Industry 4.0 [2][3][4]. CPSs are a fusion of networks, computation, and physical environment in which embedded computing devices continuously sense, monitor, and control the physical environment [5]. CPS represents one of the most important accomplishments in the development of ICT [6]. A simple view of a cyber-physical system (CPS) architecture is illustrated in **Figure 2**. 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 [7][8].

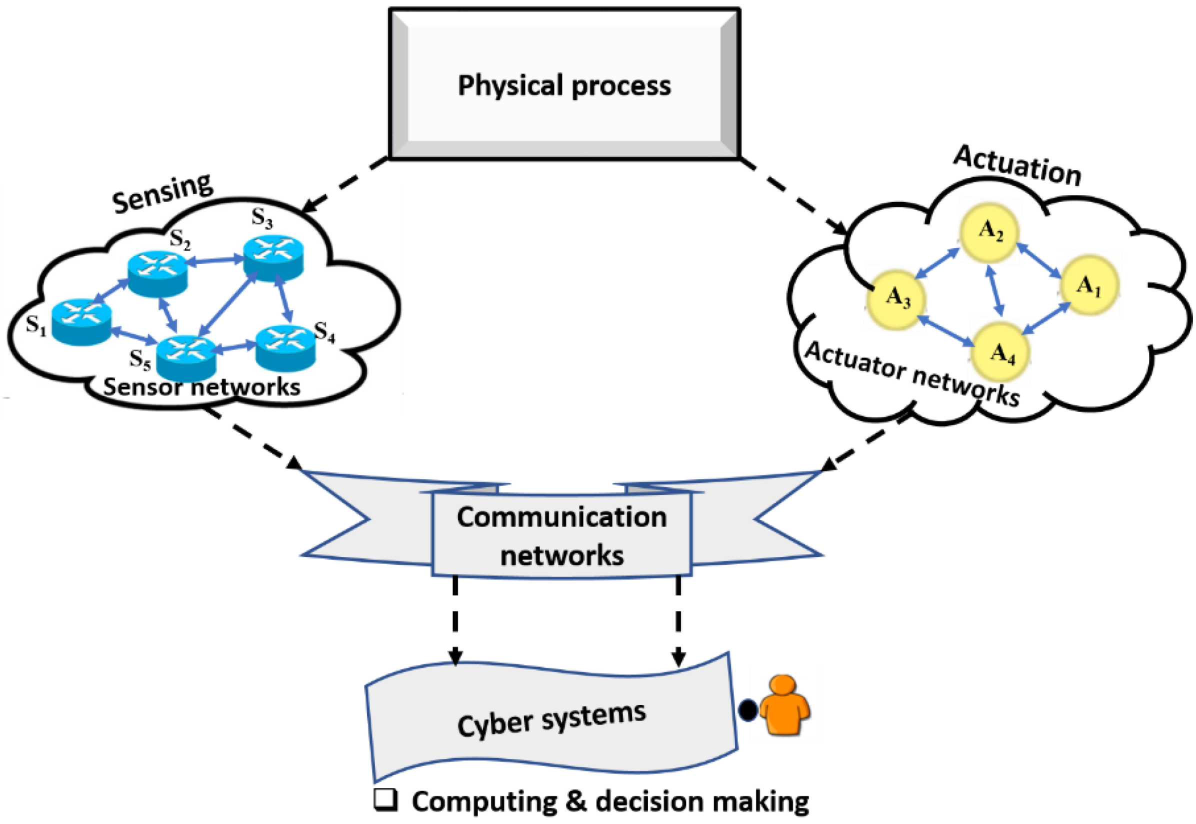

Figure 2. A simple view of CPS architecture [7].

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 [9] 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** [10] 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 [11], 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 [12]. 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 [13][14][15][16] 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 [17][18][19]. The research study in [17] presents a CPS framework for real-time control of the urban water cycle as illustrated in **Figure 3**. In their 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.

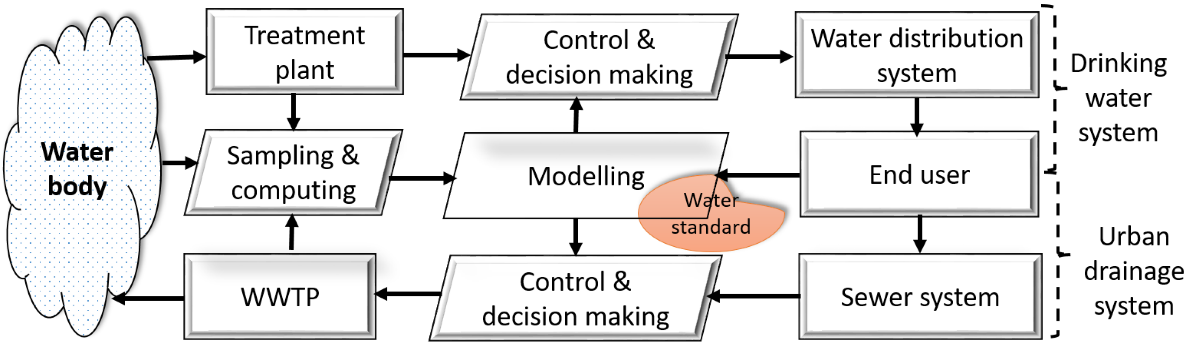

Figure 3. A CPS for the control of urban water cycle [17].

Nasir and Song [20] proposed a CPS architecture for in-pipe water quality monitoring. The proposed system illustrated in **Figure 4** 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. [21] developed low-cost real-time monitoring and contaminant detection in a drinking water distribution system. In [22], 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 [10] 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 [23][24][25].

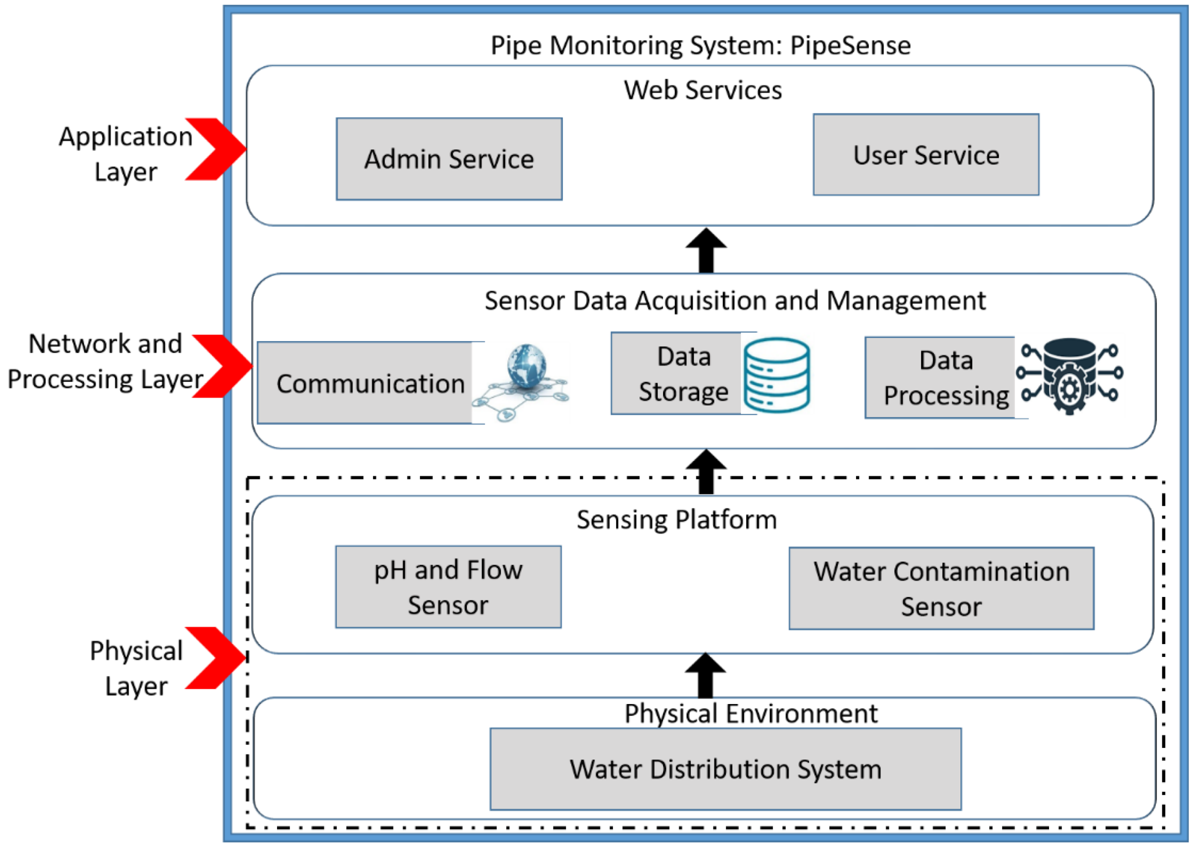

Figure 4. Architectural framework for in-pipe water monitoring system [20].

3. 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 [1][2][26]. Most notably, IoT has aided smart factories [27]. 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 water supply systems (WSS) is controlled with the use of supervisory control and data acquisition systems (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 [28] 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 5**). 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** [29]. 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) [28]. Thus, the use of IoT in the water sector is increasingly gaining momentum.

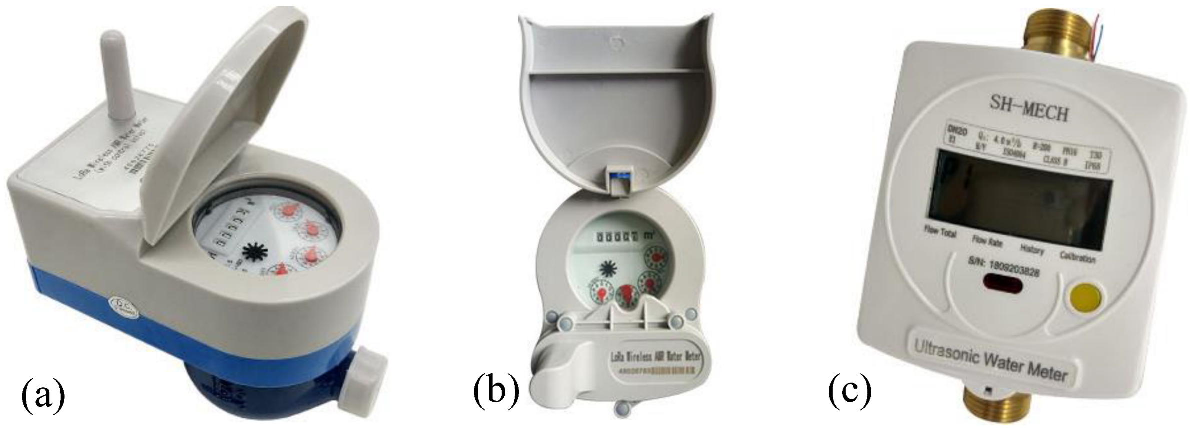

Figure 5. Samples of AMR water meters with LoRa communication technology (**a**) LoRa remote water meter; (**b**) electronic remote valve control water meter; (**c**) wireless ultrasonic LoRa water meter [29].

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

LoRa Water Meter Class	LoRa Remote Water Meter	LoRa Electronic Remote Valve Control	Wireless Ultrasonic LoRa Water Meter
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. 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 [30][31][32]. 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 [33]. Of course, this is not constant and solely depends on the time, data types, and application type [34]. 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 [35]. 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 [35]. One area of application where big data analytics may be useful is in the support of sustainable groundwater management and water treatment facilities [36][37]. 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 [38]. 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 [33][39] 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 [40] 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 [41]. Investigation shows that it is possible to effectively monitor system data performance and post implementation for sustainability. Chalh et al. [42] 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 [43], 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 [44][45][46][47]. 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.

5. 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 [48]. Some of the potentials of AI in the water sector are shown in **Figure 6**.

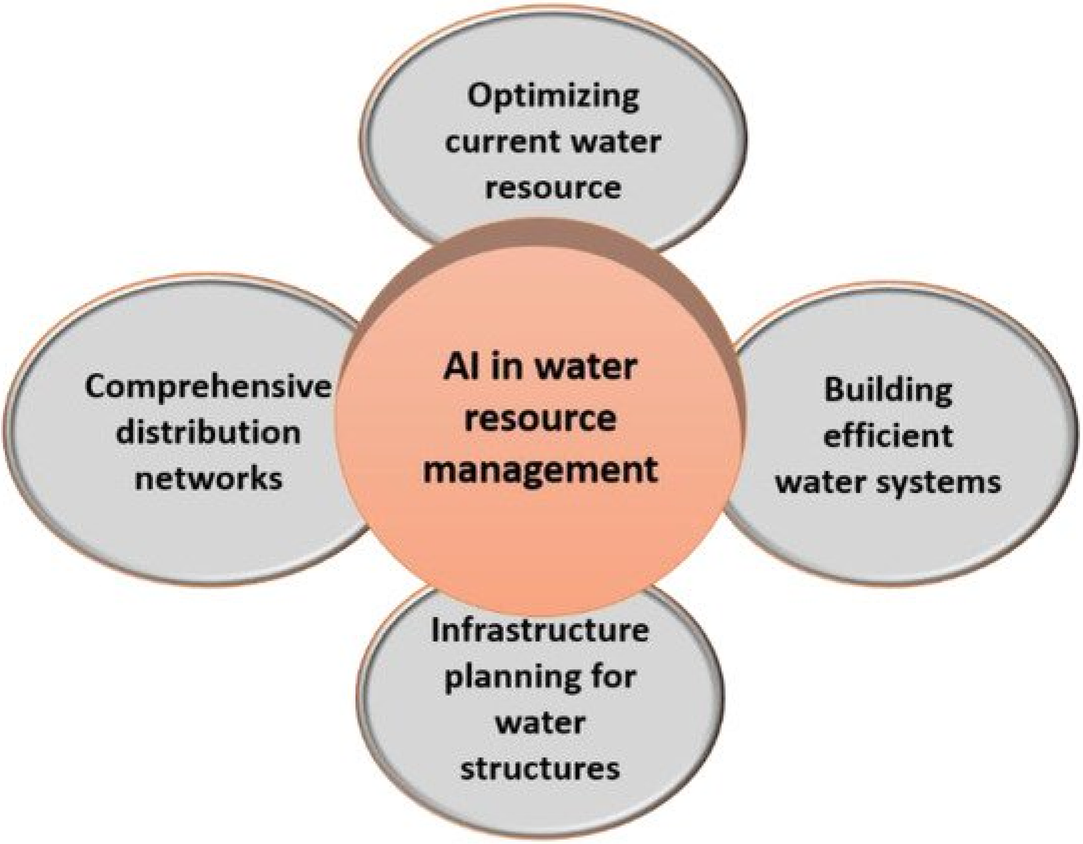

Figure 6. Some of the potentials of AI in the water industry.

The optimization of current water resources can be achieved with the decision-making abilities of AI, where decision support systems [49][50][51][52] 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 [53][54][55][56], 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 [57][58][59]. One such application is the estimation of the likelihood of event occurrence and the raising of corresponding alarms using Bayesian networks [58]. Elsewhere [57], 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 [60]. 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 [61][62][63][64]. In this application, the water quality index (WQI) and water quality classification (WQC) may be achieved as illustrated in **Figure 7**.

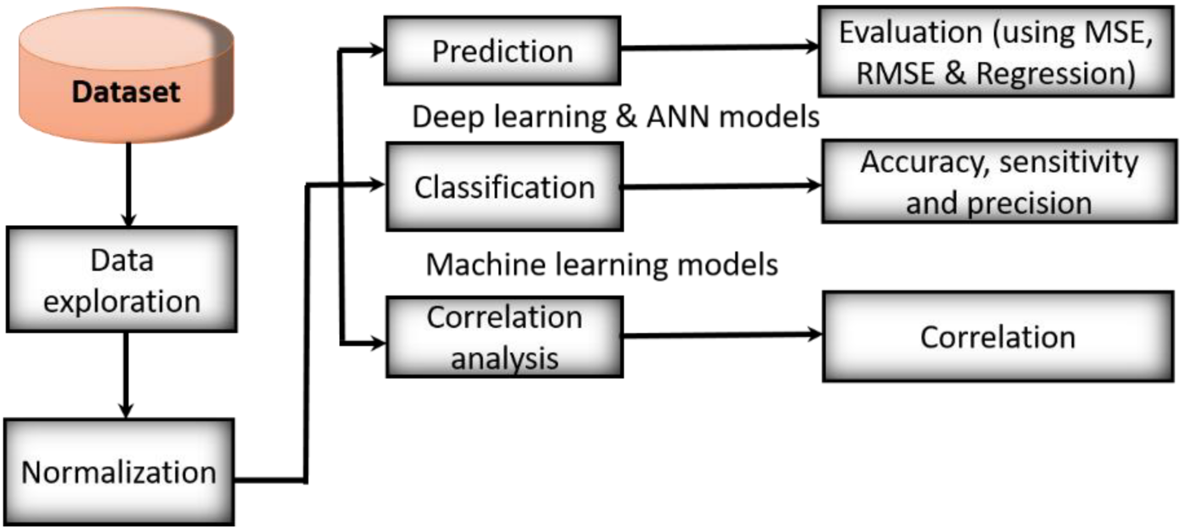

Figure 7. A framework for the application of AI for water quality monitoring [61].

In Aldhyani et al. [61], 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 [65], combining it with cutting-edge control devices allows for quick intervention and a reduction in the risk of contamination. Ahmed et al. [66] 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. [67] 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 water distribution networks (WDNs) prove its potential for sustainable management of WDNs with 95% detection accuracy. The studies conducted in [68] 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 [69] 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. [70], an adaptive intelligent dynamic technique was developed for water resource planning. A computational intelligent system was proposed by [71] 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.

6. 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 [72]. Cloud-based computing technologies can make a significant contribution to Water 4.0 realization. Cloud computing has powerful storage, processing and service ability [73]. 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 [7]. 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) [74][75][76], leak detection [77], pressure control and monitoring (PCM) [78], state estimation and monitoring (SEM) [79][80], demand prediction and monitoring (DPM) [81], pipe health monitoring (PHM) [82], water resource management (WRM) [83]	Mostly employed	Success rate depends on the sensing and communication devices used.
IoT	Smart sensing, data processing and communication	Leak detection [84][85], WQD [86], PHM [87][88], pressure monitoring [89], WRM [90]	Most employed	Success rate depends on the sensing and communication devices used.
BD Analytics	Smart sensing, data analysis and decision making	Leak detection [91], WRM [92][93]	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 [94][95], PHM [96][97], DPM [98][99], process automation for water treatment and desalination [100][101]	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 [102][103], WQD [104][105].	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 [106] 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 [107][108].

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