An Overview of the Applications of Artificial Intelligence in Water Engineering

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Abstract- Access to clean water and sanitation is essential for all aspects of human life. The integration of artificial intelligence and data analysis can provide more efficient methods for water treatment and improve human well-being. These advancements can aid in identifying harmful micro-organisms and other contaminants in water, as well as reducing the negative impact of wasteful practices on various industries. The use of artificial intelligence in the water industry can enhance the accuracy and effectiveness of water management and sanitation aid provision. This article focuses on the sustainable development goals of the United Nations, the measurement of water variables, and the interaction of artificial intelligence with itself. Additionally, the existing water and wastewater treatment procedures, water supply optimization tools, and decision-making processes in the water industry that utilize artificial intelligence are well-documented. The study concludes that artificial intelligence can significantly contribute to improving vital parameters in water treatment, supply, and general water utilities worldwide..

Keywords Application, Artificial intelligence, Data Science, Big Data, water engineering.

1. Introduction

Access to clean water and sanitation is a fundamental aspect of human dignity. The combination of data analysis and artificial intelligence can offer more efficient methods for water treatment. These advancements can aid in detecting harmful germs and pollutants in water and minimizing the impact of wasteful practices across multiple sectors. Artificial intelligence (AI) can also enhance water-use efficiency and provide precise guidance for distributing sanitation assistance.

The emergence of "intelligent" data-driven applications has transformed our daily practices. This digital technological advancement offers significant benefits to water providers willing to innovate. By leveraging artificially intelligent algorithms and large data analytics, water utilities can make more efficient decisions while improving water quality, customer service, and reducing costs (Jenny et al., 2020). This article introduces AI for water treatment and utilities participating in this digital revolution and seeking to enhance their water distribution operations.

This article presents comprehensive discussions of the best methods for water purification using AI technologies for treatment and supply, including strategies and cost estimates (Jenny et al., 2020). In recent years, new approaches using artificial intelligence have emerged, leading to the development of "Responsible Artificial Intelligence" (RAI) that aligns with human and ethical principles. Although AI-based methods are not as commonly used in the water domain as in other sectors, such as energy, healthcare, or transportation, three insights have relevance to the water sector. These insights involve using AI techniques in multi-objective optimization, data-driven models that avoid pitfalls of strictly data-driven models, and applying participatory decision-making based on previous experience in the water sector.

Multi-objective optimization is critical in the water sector as it allows for the creation of a range of values while facilitating constant changes. By using this approach, water utilities can balance multiple objectives, such as maximizing water quality, minimizing costs, and improving customer satisfaction, simultaneously.

Data-driven models have become increasingly popular in recent years, but they have their limitations. Strictly data-driven models cannot take into account the complex and dynamic nature of the water sector. Therefore, it is important to use data-driven models in combination with domain knowledge and expertise to overcome their limitations and ensure that decisions are based on accurate and relevant information.

Finally, participatory decision-making based on previous experience in the water sector can enhance the effectiveness of AI-based solutions. Stakeholder engagement and collaboration can improve the design and implementation of AI-based technologies, ensuring that they are tailored to the specific needs of the water sector.

In conclusion, the application of artificial intelligence in the water sector can significantly enhance water treatment and distribution operations. The use of AI techniques such as multi-objective optimization and data-driven models, along with participatory decision-making, can improve water quality, reduce costs, and enhance customer satisfaction. As the water sector continues to face new challenges, the integration of AI technologies will be essential to ensure sustainable water management and promote human well-being.

2. Search Strategy for Relevant Literature

The authors adopted the following search strategy to obtain relevant results. First, they identified the main ideas and key search terms, such as "Application," "Artificial intelligence," "Data science," "Ethics," "Water domain," "Multi-objective optimization," "Clean water," "Water purification," "Adsorption," "Water contamination," "Algorithms," and "Membrane filtration." These search terms were used on Google Scholar and other journal search engines, such as Elsevier and Springer, based on the ideas and theories discussed in the conceptualization stage of this work.

Date and time exclusions were not made for this search, as the authors aimed to capture as many relevant articles as possible for the review. However, articles that discussed the general use of artificial intelligence were excluded from the study, as the focus was solely on how the technology could be applied in the field of water engineering.

The measurement of various water variables can be complex and costly, with susceptibility to natural disasters. Maintenance, control, and calibration processes may pose challenges in certain situations. For instance, river flow measurements are obtained using a current meter after establishing the cross-sectional area of the river channel, and the scoops used to measure river level are weighed on a level meter (scale) in the stream section under consideration. Regression analysis and its results are widely applied in practice to determine flow rates and other factors. The use of evapotranspirometers (lysimeters) is a common method for monitoring evapotranspiration (Ay & Özyıldırım, 2018) [3]. Salinity, electrical conductivity, and other water quality measurements are also important, but variables like water quality and time series length are monitored at non-systematic intervals, leading to missing data sets and difficulties in data analysis. International water quality regulating bodies, such as the Environmental Protection Agency (EPA), Water Pollution and Control Regulation (WPCR), and World Health Organization (WHO), have established standards for measuring and determining water quality for various uses (Ay & Özyıldırım, 2018) [3]. Potassium, phosphate, biological oxygen demand, faecal coliform, temperature, calcium, chemical oxygen demand, pH, dissolved oxygen, nitrite, and nitrate are among the approximately 50 variables recommended by these regulatory bodies. Using the example of a comparison, the need to specify water quality with numerous factors can be demonstrated even in a single place. When all connections between water quality factors are examined, even in a single site, the analysis of numerous variables becomes complicated. However, current techniques cannot be used if several variables appear with varying frequencies in the same place (Ay & Özyıldırım, 2018) [3].

In contrast, AI techniques are employed in intermediary control components, such as valve system design, and optimization and modeling methods coordinated with other fields of research have been used in many engineering projects to improve their efficiency and long-term viability (Ward, 2007; Tayfur, 2017, Ay & Özyıldırım, 2018) [3,18,19]. The use of AI methods to forecast hydrologic factors based on inaccessible data is an active area of research (Ay & Özyıldırım, 2018) [3]. Hence, the use of AI techniques in water resources is crucial and much-needed, and practical methods for their development must be adopted. These advancements enable computer technology, data management, visualization, and information sharing. The necessity for precise regionalization models is highlighted by the use of defective regionalization models to estimate water variable time series in unmeasured watersheds. Therefore, many ways should be used to improve the use of AI techniques in water resources. (Ay & Özyıldırım, 2018) [3].

Furthermore, AI techniques can be used to optimize the design and operation of water treatment plants. For example, AI-based algorithms can be used to optimize the dosage of chemicals used in water treatment, as well as the operation of pumps and valves (Tayfur, 2017) [19]. AI techniques can also be used to monitor water quality in real-time. By using sensors and machine learning algorithms, it is possible to detect contaminants in water and take corrective action before they become a major problem (Ward, 2007) [18].

The use of AI techniques in water resources management has the potential to improve the efficiency and accuracy of various tasks, ranging from data analysis and modeling to the design and operation of water treatment plants. Although there are some challenges that need to be addressed, such as the need for high-quality data and the development of appropriate algorithms, the benefits of using AI in this field are significant. As such, it is important for researchers and practitioners to continue exploring the applications of AI in water resources management and developing practical methods for its implementation.

3. Artificial Intelligence and the Sustainable Development Goals (SDGs)

Access to clean water and sanitation is a fundamental element of human dignity. Combining data analysis and artificial intelligence has the potential to provide more efficient methods for water treatment. With these improvements, dangerous germs and pollutants in water can be identified, and wasteful practices can be minimized in various areas. AI can also improve water-use efficiency and provide accurate guidance for the distribution of sanitation assistance, ultimately contributing to achieving SDG6.

Water resources management is critical for sustainable development, which involves the interplay of environmental, economic, and social factors. The availability of water and supportive services is essential for poverty reduction, economic growth, and environmental protection. It is therefore imperative to leverage all available technologies, including AI, to realize its potential. This includes integrating infrastructure, data management, and communication within a collaborative ecosystem of technical and cognitive resource sharing.

It is also important to recognize the challenges that water may face, including impediments, abuse, evaporation, and unavailability. Therefore, AI is also working to overcome these obstacles in delivering intelligent water management services, infrastructure, and data to effectively meet the targets of SDG 6. Ultimately, the ability to flow like water is essential to address weaknesses in infrastructure.

SDG 6 aims to ensure access to clean water for everyone, while SDG 13 focuses on reducing the adverse effects of climate change. By leveraging AI in water resources management, we can effectively address both these goals and promote sustainable development.

4. Contemporary Water and Wastewater Treatment Methods

4.1. Coagulation and Flocculation

Water treatment, wastewater treatment, and drinking water treatment are critical processes that rely on coagulation and flocculation (Prabhakaran et al., 2020; Bello et al., 2014) [4,17]. Coagulation and flocculation are essential processes in various fields, and water clarification with coagulating chemicals has been practiced for centuries in potable water treatment. The use of almonds to purify river water was documented as far back as 2000 BC by the Egyptians, while the Romans documented the use of alum as a coagulant in 77 AD (Bello et al., 2014; Mohindru et al., 2017) [4]. By 1757, the use of alum as a coagulant in water treatment had become a common practice in many cities.

In the United States, the regulatory limit for treated water turbidity has progressively decreased from 1.0 NTU in 1989 to 0.3 NTU today, with many water utilities striving to maintain treated water turbidity levels of less than 0.1 NTU to minimize the risk of pathogen contamination (Prabhakaran et al., 2020) [17]. Most water treatment techniques rely on coagulation and flocculation, which involve the use of flocculants such as ferric chloride and aluminum, and coagulants like ferric chloride and aluminum (Prabhakaran et al., 2020; Martini & Roni, 2021) [13,17]. The efficiency of this process depends on several factors such as the dose of flocculant and coagulant agents, initial targeted pollutants concentration, and pH solution (Bello et al., 2014) [4]. The principles of entrapment, destabilization, and aggregation or flocculants binding are involved in this process.

However, there are other risks associated with coagulation and flocculation, such as the high cost of flocculants and coagulants. Therefore, alternative techniques and technologies are being explored to minimize the costs and improve the efficiency of water treatment processes.

4.2. Membrane Filtration Method

This is referred to as membrane filtration, which utilizes synthetic polymeric membranes to remove particles smaller than about 10–2 mm, that are too small to be trapped by sand filters. The membrane functions as a sieve, making membrane filtration a more advanced water treatment technique than other methods. It produces treated water with an exceedingly high level of purity that can be reused for various purposes, including irrigation, water treatment, and even drinking water (Martini & Roni, 2021) [13].

Based on their size and nature, particles are classified into ultrafiltration, microfiltration, reverse osmosis, and nanofiltration (Fane et al., 2011) [9]. While the membrane filtration technique is widely utilized for water treatment, it has shown exceptional results in reducing the use of oils, dyes, and heavy metals. However, membrane materials are susceptible to fouling during operation, where pollutants accumulate on membrane holes and reduce permeate flow (Martini & Roni, 2021) [13]. Reducing fouling rates is a multi-step process that includes a cleaning procedure, a preliminary process, and system optimization.

4.3. Biological Method

Several studies have supported the use of biological wastewater treatment for nitrification-denitrification and phosphorus removal. Optimal plant design and operating conditions, combined with biological wastewater treatment, ensure excellent effluent quality in nitrates, ammonia, and phosphates. The latest European wastewater treatment standards set limits for total phosphorus and nitrogen concentrations of 1-2 mg/L and 10-15 mg/L, respectively (Elsevier, 2014; Martini & Roni, 2021) [8,13]. Reclaimed water quality monitoring is often required in situations where the risk of public exposure to the effluent exists. The management process is guided by information about incoming pollutants, especially total suspended solids (TSS) and chemical oxygen demand (COD) (Dialynas & Diamadopoulos, 2008) [7].

The biological approach to degrade pollutants in wastewater involves various microorganisms, including fungi, bacteria, yeast, and algae. Although it has some disadvantages such as longer response time and larger treatment plant area, several simple, ecologically friendly, and cost-effective alternatives exist, such as trickling filters and activated sludge. Biological agents can be classified as aerobic or anaerobic (Mishra & Maiti, 2020; Pang & Abdullah, 2013; Gómez-Ramrez & Tenorio-Sánchez, 2021) [10,14,16].

4.4. Adsorption Method

There are various particulate constituents that depend on the pollutant, including grease and oil colors, natural and organic matter, metal ions, non-organic chemicals, and even particles dissolved in the adsorbate layer. Different types of adsorbents are widely used in various industrial wastewater treatment facilities, including activated carbon, biochar, and chemically modified adsorbents. Adsorbent materials can be synthetic, organic, or inorganic. Some efforts are made to use natural materials to preserve environmental sustainability. Certain natural materials, such as banana peels, eucalyptus bark, barley straw, orange peels, watermelon peels, and others, can absorb different types of pollutants, including particulate matter or metals like aluminium, from the given environment (Martini & Roni, 2021) [13].

5. Advanced Oxidation Processes (AOPS)

Conventional techniques are no longer just an additional treatment option but also a cost-effective alternative to advanced oxidation processes (AOPs). Applying AOPs to wastewater biodegradation as well as pathogen inactivation is very common. By converting pollutants into safe goods, the pollutants may produce water, carbon dioxide, and other products. Scientific studies have shown that these strategies effectively combat specific contaminants (Martini & Roni, 2021) [13]. Even so, these techniques have many shortcomings, such as expensive chemical use and its after-use effects, the creation of sludge, and the production of by-products. Table 1 below shows the disadvantages and advantages of some water management methodologies.

Table 1. Advantages and Disadvantages of some Water Treatment Methods Source: [6]

	Physical or Physicochemical Treatment	Biological Treatment	Chemical Treatment
Kind of pollutant	Industrial (organic, inorganic, metals)	Industrial and domestic (low concentrations of organic and some inorganic)	Industrial (organic, inorganic, metals)
Methods	Filtration Adsorption Air flotation Extraction Flocculation Sedimentation	Anaerobic Aerobic Activated muds	Thermal oxidation (combustion) Chemical oxidation Ion exchange Chemical precipitation
Advantages	Low cost of capital Relatively safe Easy to operate	Easy maintenance Relatively safe elimination of the dissolved contaminants Easy to operate	High degree of treatment Elimination of the dissolved contaminants
Disadvantages	Volatile emissions High energetic cost Complex maintenance	Volatile emissions Require elimination of residual muds Susceptible to toxins or antibiotics	High costs of capital and operation. Difficult operation

6. Integrated Approach

There is no single wastewater treatment process that can provide sufficiently treated water on its own. Adsorption, membrane filtration, flocculation, and coagulation all have drawbacks that must be addressed (Bello et al., 2014) [4]. Many studies have shown that integration can enhance the process, resulting in better wastewater treatment results with improved treatment machines and other treatment media conditions (Martini & Roni, 2021) [13]. The hybrid of adsorption using hybrid activated carbon powder and membrane filtering was previously tested and found to be reliable and satisfactory. In lower concentrations, powdered activated carbon may better distribute the circulation. Under this kind of shear force, the membrane is less likely to rupture. The thick cake layer may decrease the thickness of the cake, resulting in a low fouling rate and excellent pollutant removal efficiency. Dual membrane processes may be drawn from the same technology base, for example. Reverse osmosis membranes and ultrafiltration are being explored to treat wastewater containing oil due to high initial oil and chemical oxygen demand (COD) content. In conclusion, a dual membrane system can obtain approximately 7% of permeate flow decreases with free suspended material, high Total Organic Carbon (TOC), and cation removal in treated wastewater (Martini & Roni, 2021; Bello et al., 2014) [4, 13]. The creation of an integrated system that includes two or more therapeutic techniques has many benefits. Other advantages of sophisticated treatment procedures include better water and wastewater quality and safer working conditions for expensive and complicated machinery like membrane filtration facilities. Before entering the polymeric ultrafiltration membrane, the wastewater treatment process (via advanced oxidation) reported a significant fouling rate decrease, resulting in a lower washing rate and longer membrane lifetime (Martini & Roni, 2021) [13]. Figure 1 illustrates how an integrated wastewater treatment system uses Advanced Oxidation Processes (AOP) and Membrane Filtration (MF). Several particulate constituents depend on the pollutant, including grease and oil colors, natural and organic, metal ions, non-organic chemicals, and even particles dissolved in the adsorbate layer. Several adsorbents are well-known in different industrial wastewater treatment facilities, including activated carbon, biochar, and chemically modified adsorbents. Adsorbent materials that are synthetic, organic, or inorganic can be used. Attempts have been made to use natural materials to preserve environmental sustainability. These materials can take up different kinds of pollutants, including particulate matter or metals, such as aluminum, from a given environment by using certain natural materials like banana peels, eucalyptus bark, barley straw, orange peels, watermelon peels, and the like (Martini & Roni, 2021) [13].

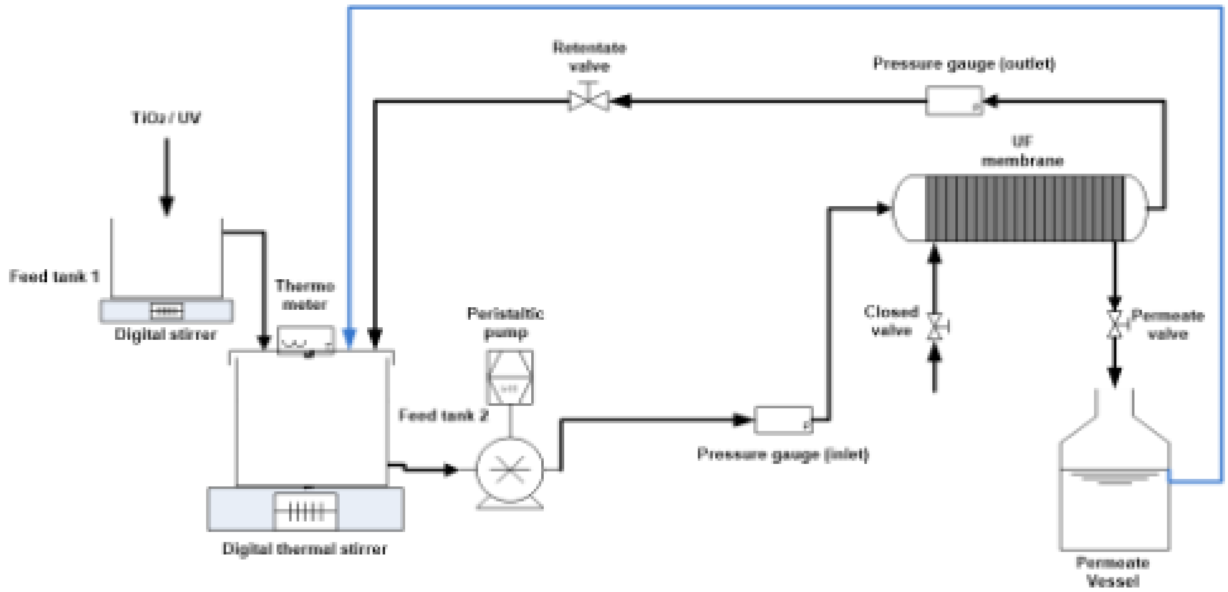

Fig. 1. Advanced Oxidation Processes (AOP) and Membrane Filtration (MF) used in an integrated wastewater treatment system. Source [13].

7. Artificial Intelligence

The concept of artificial intelligence originated from the belief of ancient Greek, Indian, and Chinese thinkers that human thinking could be automated (Alam et al., 2022) [1]. In contrast to previous centuries, when philosophers aimed to formalize argumentation for computation, efforts in the early 19th century focused on developing programmable computers.

Significant progress in fields such as mathematics, psychology, engineering, economics, and neurology during the first half of the 20th century, including advances in code-breaking machines that helped the allies win World War II, set the stage for the emergence of artificial intelligence as a field of study (Alam et al., 2022) [1].

The Dartmouth Summer Research Project on Artificial Intelligence in 1956 (John McCarthy et al., 2006; Alam et al., 2022) [1,12] marked the beginning of the first wave of artificial intelligence. The second wave of artificial intelligence began around the start of the 21st century, with statistical models trained on "big data." While these models had classification and prediction abilities, they lacked contextual capacity and had limited reasoning skills (Alam et al., 2022) [1]. Second-wave AI algorithms can recognize a cat from a photograph, but they cannot explain why the image contains a cat. Statistical learning dominates in this method due to the significant development of machine learning, including deep learning and evolutionary computation, over the years (Alam et al., 2022) [1].

Machine learning algorithms start by creating a mathematical model based on "training data" - examples or examples of the thing being modeled (Al-Daoud, 2009) [2]. Deep learning, a subset of machine learning, is particularly effective with unstructured or unlabeled data. Evolutionary computation, which utilizes evolution, produces a family of global optimization methods based on biology. Genetic computing, a part of evolutionary computing (Alam et al., 2022), uses biological operators like mutation, crossover, and selection to produce a "population" of solutions. The population's fitness quality progressively improves with each new generation, which involves eliminating less wellperforming solutions and adding minor random modifications (Alam et al., 2022) [1].

Second-wave AI methods are often referred to as black boxes that rely on the quality of training data. The third wave of AI methods, supported by DARPA, aims to address this issue and develop "white box AI" that can adapt contextually (Alam et al., 2022) [1]. Third-wave AI methods understand context and meaning well and can dynamically adjust. These techniques can identify a cat and describe the process they used to conclude that it was a cat. This project may help solve the "black box" nature of current machine learning methods. Another positive aspect of third-wave AI methods is that they rely less on extensive training sets.

This new application of artificial intelligence has introduced several elements, such as waste management, resource extraction, wastewater treatment, and reuse. Digital machine learning has been used in wastewater treatment to aid prediction and optimization. Alam et al. (2022) [1] aimed to obtain more accurate and reliable real-world calculations to assist chemicals with adsorption or advanced oxidation in wastewater treatment. Using artificial intelligence, targeted pollutants' removal can be simulated, predicted, confirmed, and optimized in wastewater treatment systems.

Additionally, the use of artificial neural networks has enhanced standard kinetic and isotherm equations for arsenic removal. Martini and Roni (2021, 13) utilized O. ficus indica biomass previously activated by pyrolysis and ZnCl2 to experimentally work on arsenic adsorption and provide the output of kinetic and isotherm patterns.

Moreover, the application of artificial intelligence in the wastewater treatment process has been found to improve the accuracy of predicting and optimizing the removal of targeted pollutants. For instance, Alam et al. (2022) [1] utilized digital machine learning to enhance the prediction and optimization of chemicals with adsorption or advanced oxidation in wastewater treatment. By simulating, predicting, confirming, and optimizing the removal of targeted pollutants, artificial intelligence can help in achieving more accurate and reliable real-world calculations.

In a study conducted by Martini and Roni (2021, p. 13) [3], an artificial neural network was employed to enhance the standard kinetic and isotherm equations for arsenic removal in wastewater treatment. The researchers used O. ficus indica biomass previously activated by pyrolysis and ZnCl2 to experimentally test the output of kinetic and isotherm patterns. They combined traditional adsorption equations with the new isotherm and kinetic equations, and then tested the models using real data from arsenic adsorption. The results showed that the models using artificial neural networks worked better than the traditional equations in calculating the kinetic and isotherm adsorption equations, which can improve the design of the process.

In conclusion, the concept of artificial intelligence has its roots in ancient times, but significant progress has been made in the field since the early 19th century. The second wave of artificial intelligence, which relied on statistical models trained using big data, dominated the field at the beginning of the 21st century. However, these methods were criticized for remaining black boxes, lacking contextual adaptability, and relying on substantial training sets. DARPA's third wave of AI methods addressed these challenges and enabled the use of contextual adaptability, dynamic adjustments, and understanding of context and meaning. The application of artificial intelligence in wastewater treatment has improved the accuracy of predicting and optimizing the removal of targeted pollutants, and can lead to more accurate and reliable real-world calculations.

8. Water Supply Tools for Optimization and Decision Using Artificial Intelligence

Hydraulic models serve a variety of functions, including the use of predictive tools for planning and operating water distribution networks. These tools rely on data from a single location at a given time and are made possible through the use of clarification and forecasting techniques that enable the analysis of distribution network behavior without sensor and instrument data (Jenny et al., 2020) [11]. Decision-making in hydraulic modeling involves the use of optimization methods that search for solutions to numerical objective functions that maximize or minimize chosen parameters. Optimization methods have been used in water distribution network modeling since its inception. Nowadays, most water utilities use optimization methods due to the availability of inexpensive sensors and faster computers. Location optimization techniques can also be used to extract essential information from a small number of sensors in the water supply system. Additionally, operational analysis can be applied to optimize the operations of pumping stations' pressure or flow control valves, which saves energy and improves water quality (Jenny et al., 2020) [11].

The availability of big data has directly contributed to the development of artificial intelligence (AI), leading to an increasingly abundant and extensive data ecosystem. AI algorithms are capable of analyzing data and learning from it, thereby enhancing their effectiveness over time. Machine learning tools, which are derived from large amounts of data, coupled with techniques like decision trees, nonhierarchical classification algorithms, and Bayesian networks, are currently popular. Deep learning, a technique that has recently gained widespread recognition, has been utilized to great effect in various applications, including picture classification, speech recognition, and self-driving cars. However, there is little consensus on whether deep learning will cause similar disruption in water network analysis with corporate operations and consumer interactions. Furthermore, AI-based methods and deep learning techniques for network analysis are not presently feasible options (Jenny et al., 2020) [11].

9. The Role Big Data and AI Algorithms Play in the Water Industry

With access to big data, the following functions are possible in water systems.

9.1. Optimal Network Design

Digital monitoring and control networks have finally brought the water utility industry into the digital age.AI algorithms provide precise information-based criteria for specifying the location of sensors in a given network in order to extract the most significant quantity of information about the overall system with the lowest capital investment. (Jenny et al., 2020) [11].

Installing pressure gauges instead of flowmeters means reducing the number of control points and putting pressure gauges over flowmeters. By putting a number on network instrumentation and the operational benefits that will come from it, a realistic cost-benefit analysis framework can be set up.

9.2. Management of Asset Investment Programs

Most water utilities have a defined plan to provide optimum service levels and reduce costs by integrating maintenance and replacement. Active asset management is about responding to outside random events before they happen instead of just reacting to them when they do.Based on the asset's service life, how important it is, and other factors, algorithms help figure out the best time to check and replace assets.

9.3. Contingency Plans and Procedures

When dealing with crises, water utilities plan for everything and minimize the effect on consumers. Additionally, pipes may rupture, fail, cause power outages, water shortages, and contamination incidents. Algorithms help generate a reaction optimized for the degree of hazards (from service interruptions to health threats).

9.4. Optimal Network Expansion Planning

Advanced AI optimization technologies provide an in-depth analysis of the most cost-effective combinations in terms of the total budget and any other specified targets. AI algorithms can find the best ways to increase the size of a network. Their more solid way of making decisions is based on design parameters like predicting population growth and planning the layout of cities, which take into account the uncertainty of such parameters.

9.5. Assessment of the Types of Consumption and Forecasting Demand Patterns.

AI systems learn and improve by feeding additional data into the forecasting model. Real-time forecasts are created to aid with capacity expansion planning for the next 24 hours or beyond. It's important to keep in mind that the level of uncertainty in every prediction is based on how much historical data is available to calibrate the hydraulic model. Long-term forecasts are connected to future climatic and socioeconomic situations and are linked to how the future will turn out (user-defined).

9.6. Water Loss Detection Using Numerical Methods

To give geographical information on the quantity and type of water losses, AI methods are used with the aid of stochastic optimization and state estimation. Once the AI algorithms have given the data a level of uncertainty, they use the data to find the most likely state of the network.

They do a continuous and probabilistic calibration of the network, which allows extracting information from the error patterns (Jenny et al., 2020) [11]. This difference in density and frequency of measurement is essential in each sector of the network to make it. There are numerical locations of losses, but identifying water leaks or connections with field equipment cannot be replaced; nevertheless, it cuts costs and the time it takes to send out leak detection teams and alter distribution networks' sectorization.

Additionally, the measurements may be inspected for abnormalities, such as equipment failure. Jenny et al. (2020) [11] say that the probabilistic calibration makes the hydraulic model more accurate by figuring out the most likely pipe roughness coefficients.

9.7. Savings in Energy

First, the AI algorithms can help water network operations companies implement more efficient energy-saving operating procedures, which they use by finding the most efficient procedures while adhering to minimum service levels and energy tariff costs. Second, the algorithms can help companies identify the most cost-effective options for system upgrades to implement energy savings.

10. Challenges of the Application of Artificial Intelligence in the Water Engineering Sector

The use of artificial intelligence (AI) for achieving water-related objectives has numerous advantages and prospective benefits. However, several challenges must be taken into consideration during policy development forums. Some of these challenges are briefly highlighted below.

Developing AI applications requires access to a vast amount of high-quality, large-scale data. However, the majority of poor countries lack effective systems for collecting, storing, and distributing data on water resources. This is made even more challenging by the lack of concern for data ownership and licensing. The water sector also lacks the resources and funding necessary to promote breakthroughs and solutions, including AI. Inadequate upfront infrastructure investment, difficulty recruiting and retaining specialists, and inadequate retraining of current human resources are among the challenges faced by the water sector. (Quant crunch, 2017) [23].

A lack of capacity-building policies and practices for growing human resources who are experts in AI and water is a common roadblock in less developed nations. Additionally, there are no national or regional platforms for exchanging ideas among water professionals, technologists, and members of the general public. Meanwhile, water-related problems tend to be national or local in scope, making AI-based solutions a viable option. [24] (Schrodt, 2019).

Without a regulatory framework for AI, decisions are made on an individual basis, resulting in data and knowledge shortages. Furthermore, water sector officials and decision makers are often unaware of AI capabilities, leading to the establishment of silos for solutions and decisions. (Paul et al., 2018) [22].

Local governments, regional organizations, and universities are not doing enough to promote the use of AI to solve water-related problems. There is a lack of initiative since most organizations responsible for creating or implementing new solutions still have a mindset from the industrial age. If this structural limitation remains in place, AI will not be able to change work processes in a beneficial way (Abbosh et al., 2017) [20].

There is also a significant disparity between the northern and southern hemispheres regarding knowledge development and technology implementation related to AI and water. Developed countries are globally the top nations in AI and water research. However, not a single African nation is represented on this list. It is also true that nations in the area are not sharing their knowledge and expertise (Mehmood, 2019) [21].

11. Recommendations

The utilization of artificial intelligence (AI) for achieving water-related goals presents several advantages and potential benefits. However, policy development forums must continually consider the challenges that come with it. Some of these challenges are briefly discussed below:

One of the primary requirements for developing AI applications is having access to vast amounts of high-quality, large-scale data. Unfortunately, many poor countries still lack effective systems for collecting, storing, and distributing water-related data, aggravated by the lack of concern for data ownership and licensing. Additionally, the water sector lacks sufficient resources and funding to promote breakthroughs and solutions, including AI (Quant crunch, 2017) [23].

Other difficulties faced by the water sector include inadequate upfront infrastructure investment, difficulties in recruiting and retaining specialists, and inadequate retraining of current human resources. Furthermore, many less developed nations lack capacity-building policies and practices for developing human resources who are experts in AI and water. It is worth noting that there are no national or regional platforms for exchanging ideas among water professionals, technologists, and the general public, despite water-related problems being primarily national or local in scope, making AI-based solutions a viable option (Schrodt, 2019) [24].

The absence of a regulatory framework for AI in the water sector has resulted in judgments being made on an individual basis, resulting in data and knowledge shortages. Additionally, water sector officials and decision-makers are unaware of AI capabilities, which leads to the establishment of silos for solutions and decisions (Paul et al., 2018) [22].

Furthermore, the lack of initiative among local governments, regional organizations, and universities responsible for creating or implementing new solutions impedes the use of AI in solving water-related problems. This structural limitation must be addressed to enable AI to change work processes positively (Abbosh et al., 2017) [20].

In terms of AI-related knowledge development and technology implementation in the water sector, there is a significant disparity between the northern and southern hemispheres. Developed countries dominate AI and water research globally, with no African nation represented on the list. Furthermore, nations in the area are not sharing their knowledge and expertise (Mehmood, 2019) [21].

To address these challenges, national and regional information portals must be established to facilitate the exchange of AI-related water sector information. These portals can help people work together and spot new market trends. Moreover, holistic conversation platforms must be developed between government and industrial sectors, academia, and civil society to build comprehensive AI-based solutions that address water-related concerns. To bridge data gaps, guidelines based on public frameworks should be developed, which should apply globally to ensure decentralized data management and prevent data and data-related services from being monopolized. National and regional water agencies must develop regulations and action plans to promote the development of AI-based solutions in the water industry.

In addition, institutional development initiatives and planning processes must concentrate on mid-and long-term objectives to build human resources in AI. Capacity-building initiatives must be set in motion at higher education and vocational training institutions to address knowledge gaps. These initiatives must also be based on organizational models that can handle digital shocks, with a focus on sharing and pooling resources for capacity-building initiatives. Lastly, AI in the water industry must be connected with academia to ensure that innovations are driven by demand and meet social demands, as well as national and regional sustainability. Organizations must be encouraged to disclose trends and uses of AI in water.

12. Research Gap

While there is significant research on the applications of artificial intelligence (AI) in water engineering, there is still a research gap in the area of the development of comprehensive and integrated AI-based solutions that can address the complex and multifaceted challenges faced by the water industry. There is a need for more research that focuses on the development of innovative AI-based tools and techniques that can be used to predict, monitor, and manage water resources more effectively and efficiently. Additionally, there is a need for more research on the social, economic, and cultural implications of introducing AI into the water sector, as well as the capacity-building and infrastructure development strategies required to ensure successful AI-driven development outcomes. Furthermore, there is a need for comparative studies that evaluate the performance of different AI tools and techniques, and research that investigates the potential synergies between different AI-based solutions in water engineering. Overall, more research is needed to develop a comprehensive understanding of the potential of AI in the water industry and to address the complex challenges faced by this sector.

13. Conclusion

The application of artificial intelligence (AI) in the water sector has several advantages and potential benefits, but policymakers must also consider the challenges and limitations that exist. One major challenge is the need for access to large-scale, high-quality data, which is often lacking in many developing countries due to inadequate data collection and storage systems. Additionally, there is a shortage of human resources with expertise in both AI and water, as well as inadequate infrastructure investment and retraining of current human resources.

To address these challenges, it is recommended that national and regional information portals be established for exchanging water sector AI information, and holistic conversation platforms be built to facilitate collaboration between government and industrial sectors, academia, and civil society. Guidelines based on public frameworks should be developed to bridge data gaps, and regulations and action plans should be put in place to promote the development of AI-based solutions in the water industry.

Capacity and infrastructure development strategies should also be implemented to ensure the successful application of AI in the water sector. This includes targeting the ICT and AI requirements of all water-related stakeholders' skill development, as well as considering computing, energy, data production, and storage in infrastructure development policies. It is important to provide water sector-related education at all levels to prevent employment displacement due to AI-led innovation.

The impact of AI in the water sector is significant, with the ability to predict water-related tragedies, prevent economic damage, protect communities and ecosystems, and reduce the number of people affected by water-related diseases and disasters. However, policymakers must consider the unique social, economic, and cultural aspects of each situation and conduct a baseline assessment to determine the feasibility and return on investment of AI interventions.

In conclusion, while AI has been extensively employed in the water sector, there is still a need for further research to explore additional AI tools for improved computational capabilities and applications in water resources engineering. The comparative research of AI tools' performance should be conducted to determine the best AI tool for a particular use case.

References

[1] G. Alam, , I. Ihsanullah, , M. Naushad, , and M. Sillanpää, Applications of artificial intelligence in water treatment for optimization and automation of adsorption processes: Recent advances and prospects. Chemical Engineering Journal, 427, 130011, 2022. https://doi.org/10.1016/j.cej.2021.130011

[2] E. Al-Daoud,. A comparison between three neural network models for classification problems. Journal of Artificial Intelligence, 2(2), 56-64, 2009. https://doi.org/10.3923/jai.2009.56.64

[3] M. Ay, and S. Özyıldırım, Artificial intelligence (AI) studies in water resources. Natural and Engineering Sciences, 3(2), 187-195, 2018. https://doi.org/10.28978/nesciences.424674

[4] O. Bello, Y. Hamam, and K. Djouani, Modelling and validation of a coagulation chemical dosing unit for water treatment plants. 2014 IEEE Conference on Control Applications (CCA), 2014. https://doi.org/10.1109/cca.2014.6981433

[5] M. Chen, and M. Decary, Artificial intelligence in healthcare: An essential guide for health leaders. Healthcare Management Forum, 33(1), 10-18, 2019. https://doi.org/10.1177/0840470419873123

[6] E. M. Cuerda-Correa, M. F. Alexandre-Franco, C. Fernández-González, Advanced oxidation processes for the removal of antibiotics from water. An overview. Water, 12(1), 102, 2019. https://doi.org/10.3390/w12010102

[7] E. Dialynas, and E. Diamadopoulos, Integration of immersed membrane ultrafiltration with coagulation and activated carbon adsorption for advanced treatment of municipal wastewater. Desalination, 230(1-3), 113-127, 2008. https://doi.org/10.1016/j.desal.2007.11.020

[8] M. Fanun, The Role of Colloidal Systems in Environmental Protection, , Ed. Amsterdam: Elsevier, 2014,p.iv.[Online].Available:https://www.sciencedirect.com/science/article/pii/ B9780444632838120010

[9] A. Fane, C. Tang, and R. Wang. Membrane technology for water: Microfiltration, ultrafiltration, Nanofiltration, and reverse osmosis. Treatise on Water Science, 301-335, 2011. https://doi.org/10.1016/b978-0-444-53199-5.00091-9

[10] M. Gómez-Ramírez, and A. Tenorio-Sánchez.. Treatment of solid waste containing metals by biological methods. Natural Resources Management and Biological Sciences, 2021. https://doi.org/10.5772/intechopen.92211

[11] H. Jenny, Y. Wang, E. G. Alonso, and R. Minguez,. Using artificial intelligence for smart water management systems, 2020. https://doi.org/10.22617/brf200191-2

[12] J. McCarthy, M. L. Minsky, N. Rochester, and C. E. Shannon. A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. AI Magazine, 27(4), 2006.

[13] K. A. Roni, The existing technology and the application of digital artificial intelligent in the wastewater treatment area: A review paper. Journal of Physics: Conference Series, 1858(1), 012013, 2021. https://doi.org/10.1088/1742-6596/1858/1/012013

[14] S. Mishra, and A. Maiti, Biological methodologies for treatment of textile wastewater. Environmental Processes and Management, 77-107, 2020. https://doi.org/10.1007/978-3-030-38152-3_6

[15] J. J. Mahindra, U. K. Garg, and R. Gupta, Coagulation-flocculation technologies for arsenic removal -A review. Asian Journal of Research in Chemistry, 10(3), 405, 2017. https://doi.org/10.5958/0974-4150.2017.00069.4

[16] Y. L. Pang, and A. Z. Abdullah, Current status of textile industry wastewater management and research progress in Malaysia: A review. CLEAN - Soil, Air, Water, 41(8), 751-764, 2013. https://doi.org/10.1002/clen.201000318

[17] G. Prabhakaran, M. Manikandan, and M. Boopathi, Treatment of textile effluents by using natural coagulants. Materials Today: Proceedings, 33, 3000-3004, 2020. https://doi.org/10.1016/j.matpr.2020.03.029

[18] G. Tayfur, Modern optimization methods in water resources planning, engineering and management. Water Resources Management, 31(10), 3205-3233, 2017. https://doi.org/10.1007/s11269-017-1694-6

[19] F. A. Ward, Decision support for water policy: A review of economic concepts and tools. Water Policy, 9(1), 1-31, 2007. https://doi.org/10.2166/wp.2006.053

[20] O. Abbosh, P. Nunes, V. Savic, and M. Moore, The big squeeze: How compression threatens old industries. MIT Sloan Management Review, March 2017. https://sloanreview.mit.edu/article/the-big-squeeze-how-compression-threatens-old-industries/

[21] H. Mehmood, D. Liao, and K. Mahadeo, A review of artificial intelligence applications to achieve water-related sustainable development goals. 2020 IEEE / ITU International Conference on Artificial Intelligence for Good (AI4G), 2020. https://doi.org/10.1109/ai4g50087.2020.9311018

[22] A. Paul, C. Jolley, and A. Anthony. Reflecting the past, shaping the future: Making AI work for international development. U.S. Agency for International Development, May 2021. https://www.usaid.gov/digital-development/machine-learning/AI-ML-in-development

[23] The quant crunch: How the demand for data science skills is disrupting the job market. 2017. BHEF. https://www.bhef.com/publications/quant-crunch-how-demand-data-science-skills-disrupting-job-market

[24] P. A. Schrodt, Artificial intelligence and international relations: An overview. Artifical Intelligence and International Politics, 9-31, 2019. https://doi.org/10.4324/9780429033575-2