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Review

A Bibliometric Analysis and Review of Resource Management in Internet of Water Things: The Use of Game Theory

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Abstract: To understand the current state of research and to also reveal the challenges and opportunities for future research in the field of internet of water things for water quality monitoring, in this study, we conduct a bibliometric analysis and a comprehensive review of the published research from 2012 to 2022 on internet of water things for water quality monitoring. The bibliometric analysis method was used to analyze the collected published papers from the Scopus database. This helped to determine the majority of research topics in the internet of water things for water quality monitoring research field. Subsequently, an in depth comprehensive review of the relevant literature was conducted to provide insight into recent advances in internet of water things for water quality monitoring, and to also determine the research gaps in the field. Based on the comprehensive review of literature, we identified that reviews of the research topic of resource management in internet of water things for water quality monitoring is less common. Hence, this study aimed to fill this research gap in the field of internet of water things for water quality monitoring. To address the resource management challenges associated with the internet of water things designed for water quality monitoring applications, this paper is focused on the use of game theory methods. Game theory methods are embedded with powerful mathematical techniques that may be used to model and analyze the behaviors of various individual, or any group, of water quality sensors. Additionally, various open research issues are pointed out as future research directions.

Keywords: artificial intelligence; water research; water quality monitoring; water resource management; game theory; water system resource management; internet of water things

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1. Introduction

Water is life and is the greatest blessing to humanity on earth [1,2]. Therefore, water research is a critical area of research as water needs to be highly managed for it not to create issues for humanity, and for it to be useful for many purposes. For example, water is needed by the automobile industry to produce automobiles, and water is needed by humans to live; furthermore, water is required by the agriculture industry for irrigation, for the production of adequate food, for food security, and for wealth and prosperity creation [3]. Interestingly, these areas of life need a large amount of clean water to achieve an expected quality of life.

Unfortunately, it is highly demanding and costly to achieve safe water as a consequence of several water challenges arising from anthropogenic activities due to industrialization and urbanization, as well as population growth and natural events, for example, climate change [1,4]. Generally, water sources often suffer from a lack of necessary protection that makes them vulnerable to several anthropogenic (i.e., man-made) activities that could result in water contamination.

An example includes the discharge of wastewater into water sources without the removal of contaminants [5]. Such man-made activities substantially affect the physical, chemical, and microbiological characteristics of water, and the ingestion of such water is highly harmful to health due to contamination, such as the presence of microorganisms (e.g., Escherichia coli (*E. coli*) [6–8] and metal ions (e.g., mercury, cadmium, chromium, arsenic, and lead) [9–14]. Other sources of water contamination are natural events, such as global warming and soil erosion. Natural events occur due to changes in the climate, weather, and other natural processes. The aforementioned conditions are greatly responsible for contaminating water sources, such as groundwater, rivers, and reservoirs.

Water from water sources that are contaminated is regarded as poor quality. Such water is obviously harmful to public health and the environment; thus, it is unsuitable for various uses [15]. For example, unclean water is not safe for irrigation, as such a practice would contaminate irrigated land, agricultural produce, and the consumers of such agricultural produce. Additionally, water-borne diseases are detrimental results of drinking unclean water as they cause a large loss of life globally. For instance, according to the World Health Organization (WHO) report of 2022 [16], about 829,000 people die each year because of the use of unclean water that transmits several diseases (e.g., typhoid, polio, intestinal worm infections, and diarrhea). Similarly, due to the high toxic properties of the aforementioned metal ions, these ions cause severe health problems, including acute hepatic and renal failure, organ damage, cancer, and epigastric pain [17–19]. In addition, as a result of the contaminants that are present in water, water industry facilities, such as pipelines and equipment, are affected by corrosion, which results in leakages, water loss, and water scarcity [20–22].

If water is properly managed using cost-effective and self-sustained water quality monitoring and contaminant detection technologies, it will improve the quality of life of the human population. It will increase access to clean water for all municipalities of a country; prevent water scarcity as well as loss of money from water losses, facility repairs and replacements; alleviate poverty; increase food production and food security. Furthermore, it will promote positive effects on climate, and increase the economic prosperity of South Africa [5,23]. Hence, a key strategic priority identified by the United Nations is to monitor water systems, including water sources, pipe networks, pumping stations, and treatment plants; to detect changes in water quality and control contamination to improve the quality of life of humans, plants, and marine animals; and to prevent the distribution of contaminated water and water losses [24].

In practice, conventional laboratory-based systems, such as inductively coupled plasma mass spectrometry (ICP-MS), pH metric determination, optical infrared spectroscopy, optical spectroscopy, and impedance spectroscopy [25–28], are employed as the gold standard to monitor changes in water quality and to detect whether contaminants are present in water. These methods involve collecting water samples from water sources and transporting them, by field officers, to far-off laboratories, where the samples are studied and analyzed. Unfortunately, these methods are well established as being ineffective in terms of accuracy, sensitivity, cost, timeliness, and efficiency, as most water parameters are best measured in situ [29,30].

Considering the challenges of conventional laboratory-based methods, the use of point-of-need technologies is now gaining more attention from the industry and academia over conventional methods to achieve effective monitoring and treatment of water [31–33]. This includes the design of internet-of-things-based water quality monitoring systems. These systems are also referred to as the internet of water things (IoWT) or smart water quality monitoring systems [1]. They are used to characterize water quality based on the data generated by water quality sensors deployed in a water body, and to acquire and transmit this data [29,30], as described in Figure 1.

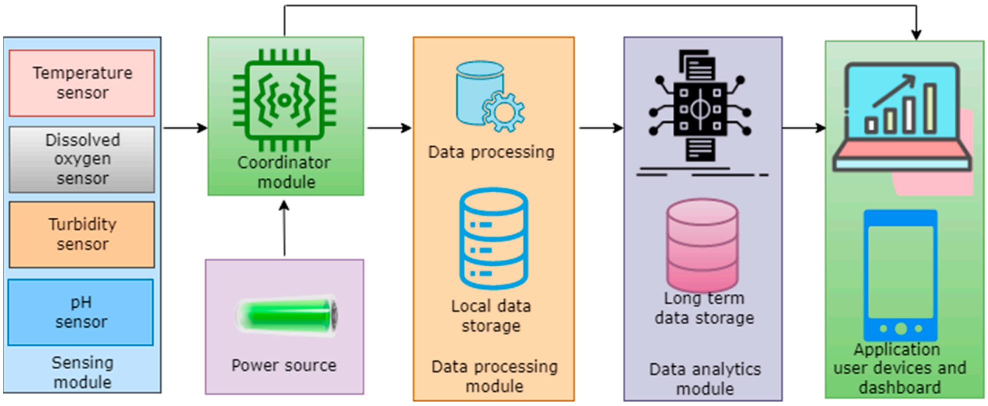

Figure 1. A typical example of internet of water things.

The design of IoWT is critical to efficiently monitor changes in water conditions, improve the health and wellbeing of humans and marine animals through the provision of access to clean water, and to clearly study and understand how changes in water quality correlate with environmental factors, including climate change.

However, the IoT water quality sensors in the IoWT network are resource-constrained devices with inherently scarce resources. These devices have two types of resources. The first type of resources are the internal resources, which include the battery power/energy resources and the computational resources. The second type of resources are the communication channel and/or radio resources (e.g., bandwidth, time slot, transmit power, channel) [29,34–36]. The IoT water quality sensor devices deployed for water quality monitoring run on battery power. Often, it may be impractical, inefficient, and costly to replace the in-built batteries of the water quality sensors after deployment. Unfortunately, as the battery power of these devices is drained, it becomes difficult for the network to sense and communicate their measurements to remote monitoring centers. Additionally, many of the sensing fields are increasingly off-grid [37]. Moreover, the battery life of most of the IoT water quality sensor devices is limited by the use of IoT radios, such as LoRa, NB-IoT, and Sigfox, due to the energy consumption during data communication, which is related to their channel access modes, sleep and wakeup operations [38]. This necessitates the need to optimize the power requirements of water quality sensors. Furthermore, the available bandwidth resources in IoT-based water quality sensing networks are scarce. For instance, most of the IoT radios (e.g., LoRa and Sigfox) used in IoT-based water systems use the already congested, unlicensed ISM frequency bands of limited bandwidth. Consequently, LoRa and Sigfox have limited bandwidths, less than 250 kHz and 100 kHz, respectively [38]. Furthermore, the NB-IoT radio uses a licensed frequency band with a limited bandwidth of about 200 kHz, for device communication [38]. This may technically impact the throughput requirements of different water quality sensors. Likewise, the processing speeds of the processors in water quality sensors may influence the data transmission delay requirements of the devices.

Following this, deploying water quality sensing networks may present some resource management challenges related to power management, bandwidth management, and time resource management [39]. What is resource management? In simple terms, resource management can be described as a process that involves the intelligent and/or optimal use of scarce or limited resources, using various resource management methods, for the purpose of improving the overall operation and performance of a system. Consequently, in the context of power efficiency of the IoT water quality monitoring systems, one of the major issues to address while implementing this type of system is the problem of water quality sensor power requirement optimization due to the limited power resources of water quality sensors. Hence, this requires that sophisticated power management algorithms are investigated and developed to optimize the power requirements of IoT water quality sensors in order to reduce energy consumption, extend device lifetime, and to also improve the energy efficiency of the network. With respect to improving the water quality communication performance of the IoT for water quality monitoring systems, bandwidth resource management is key. The water quality sensors deployed are mostly heterogeneous due to the sensing requirements, which include physical, microbiological, and chemical parameters. This often results in heterogeneous traffic with different communication throughput requirements. Due to the limited bandwidth in water quality sensing networks, efficient bandwidth resource management algorithms are required to be investigated and developed to improve the throughput of different water quality sensors. Likewise, in terms of improving real-time water quality monitoring and contamination detection, time resource management is important due to the limited number of sensors that can use the communication channel at the same time as transferring the measured water quality parameters for different water sources to the water stations. This is essential because public safety applications, such as water quality sensing, require real-time data processing and minimal data transmission delay. That is, such applications are expected to have a minimal delay in transmitting the sensed water quality data, hence, time resource management is essential to minimize the amount of time taken by water quality sensors to send their measurements. This is due to the critical nature of water quality data and the need to guarantee public safety. As a result, water quality data should be efficiently communicated to the appropriate stations to aid quick decisions on water quality status. To support the data transmission delay requirements of different water quality sensors in water quality sensing networks, efficient delay-aware time resource management algorithms are necessary to reduce the transmission delay of water quality sensor data

Due to these limitations, water quality sensing networks currently suffer from several resource management challenges, which has limited their widespread adoption. To successfully implement these technologies, the design of advanced resource management methods is essential to ameliorate power, bandwidth, and time resource impediments. Therefore, this paper is focused on the use of game theory techniques in water networks to design advanced resource management approaches in order to solve the inherent resource management constraints. Most water network resource management problems are formulated as non-convex optimization problems, and applying game theory techniques to compute the optimal and/or near-optimal solutions of these formulations for resource-constrained water networks are envisaged to improve the overall performance of such networks in terms of power consumption, throughput, and data transmission delay. Game theory is a powerful artificial intelligence method that is superior at solving resource management problems compared to optimization methods, both in terms of computational complexity and ease of implementation. Furthermore, the use of game theory will help researchers working on water technology design to develop new water monitoring systems that are sustainable and cost-effective.

The details regarding the structure of this work are as follows. Section 2 presents a bibliometric analysis and a comprehensive review of related published studies collected from the Scopus database. Section 3 presents a discussion of examples of water parameters monitored in various applications using the IoWT technology, and provides an overview of water quality sensing networks. Section 4 discusses some examples of the optimization methods used for solving resource management challenges arising in wireless communication networks. Section 5 describes the basic game theory methods for resource management challenges in water quality sensing networks. In Section 6, different examples are discussed to address resource management challenges in water quality sensing networks. In Section 7, future research directions are provided, and Section 8 concludes this study.

2. Research Design and Methodology

The review method used in this study involved three phases, namely (1) data collection of related research, (2) bibliometric analysis, and (3) a comprehensive review and analysis of the collected related works.

2.1. Data Collection of Related Research

During this phase, search engines of major scientific databases, such as Scopus, ScienceDirect, and IEEE Xplore, were used to collect the studies published over the last decade, from 2012 to the end of February 2022, based on the proposed guidelines in [40]. We input such search terms as "IoT for water quality monitoring", "Internet of Things for water quality monitoring", "resource management in IoT for water quality monitoring", etc. The purpose of this step was to carefully screen and select the important related works for a comprehensive review.

2.2. Bibliometric Analysis of the Collected Related Research

In this phase, bibliometric analysis of the collected raw data of research papers from the Scopus database was conducted for the keywords density, cluster, and timeline analysis, as conducted in [41]. These analyses are described in Figures 2–4. To achieve this, the VOSviewer [42] computer program was used to analyze the knowledge domain of the collected papers bibliometrically, using the search terms (keywords, titles, and abstracts), counting method (full counting), and type of analysis (co-occurrence). The outcomes of these bibliometric analyses allow researchers to understand the relationships among the frequency of the co-occurring keywords in the collected papers, and also to understand the core future research directions of the topics in this field.

The keyword density analysis of the collected papers on IoT for water quality monitoring is shown in Figure 2. The density analysis presented in Figure 2 shows the number of times that the keywords in the search terms appeared in the published papers over a period of time.

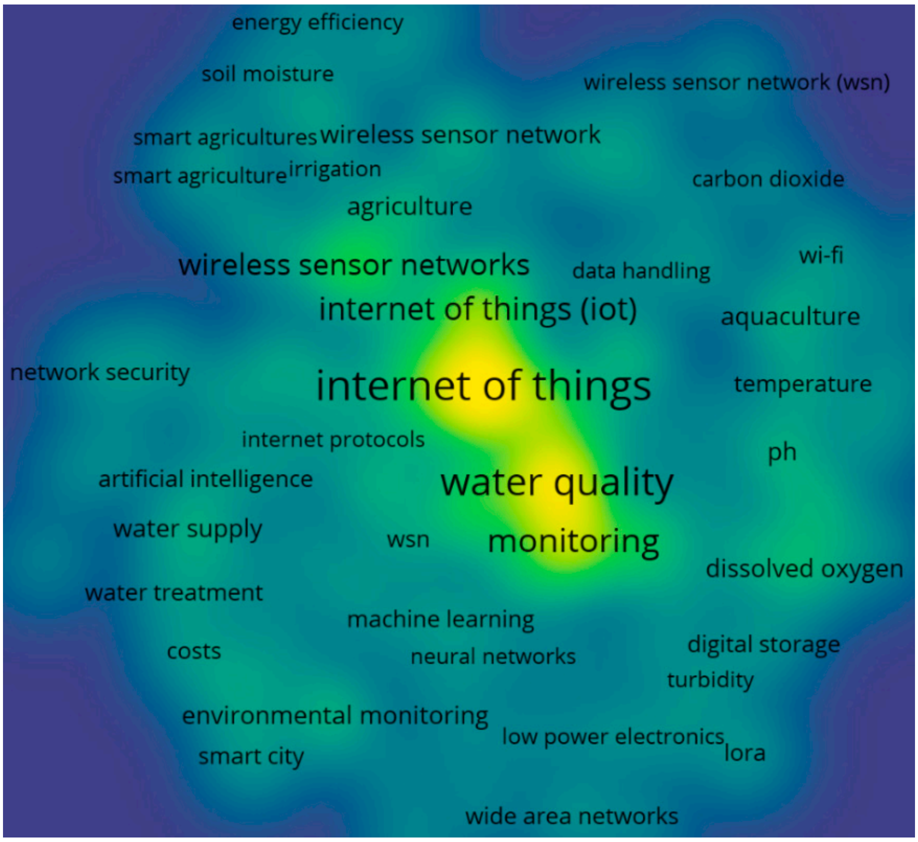

Figure 2. Density analysis of the published papers on IoT for water quality monitoring.

The keyword cluster analysis of the collected papers on IoT for water quality monitoring is shown in Figure 3. The cluster analysis presented in Figure 3 shows how a collection of keywords is grouped into multiple clusters that consist of nodes, links, and colors. The size of the nodes indicates the frequency of co-occurrence, the links indicate the co-reference, and the different colors identify individual clusters.

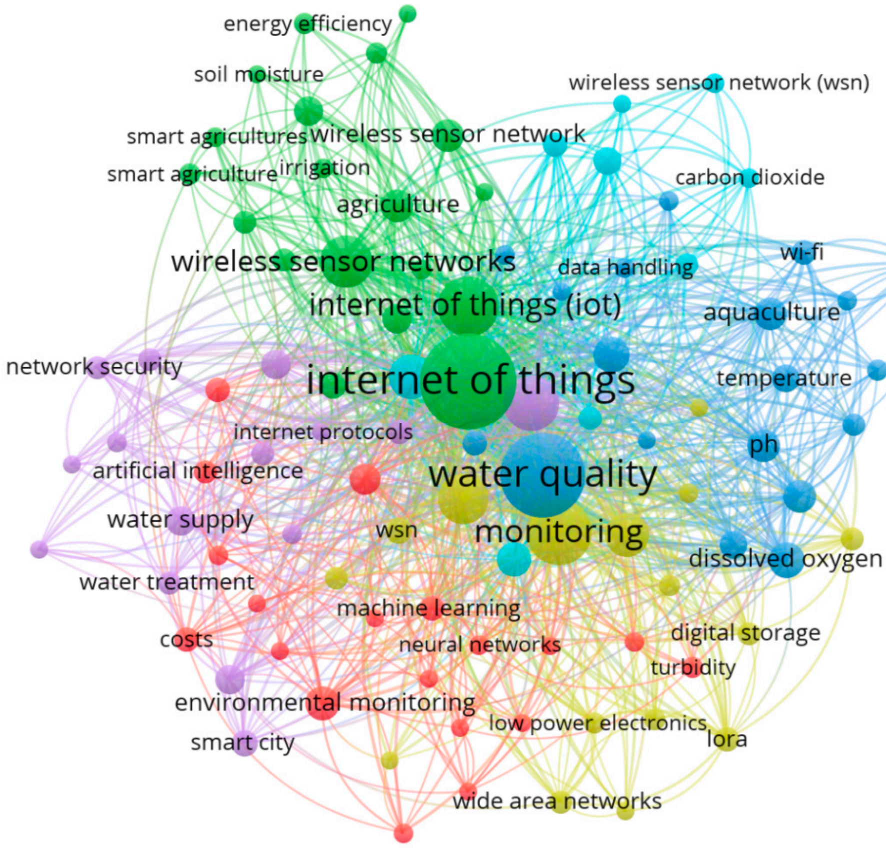

Figure 3. Cluster analysis of the published papers on IoT for water quality monitoring.

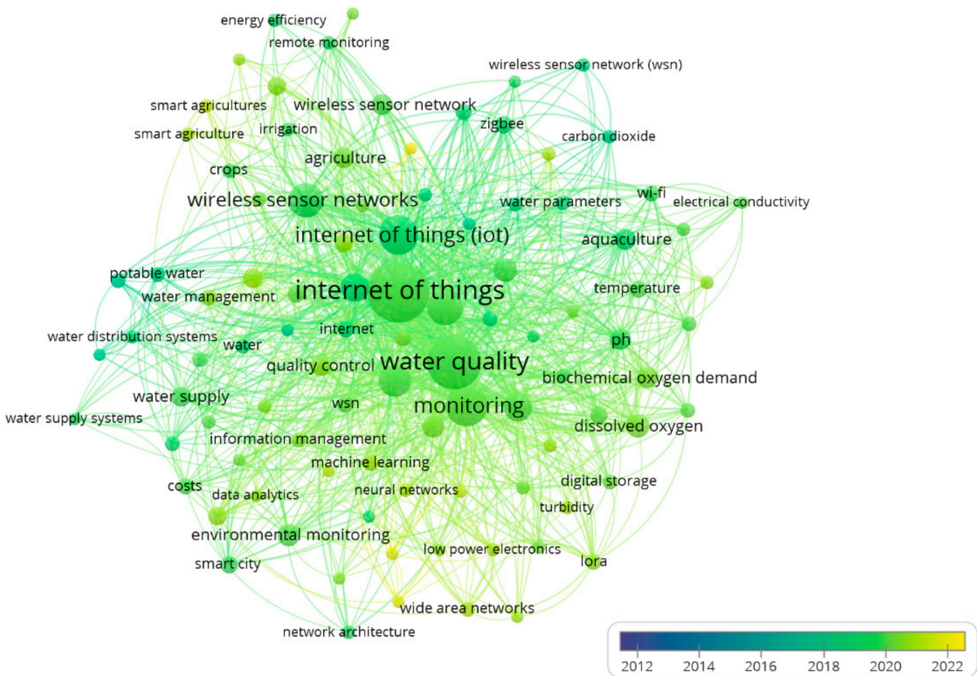

Figure 4. Timeline analysis of the published papers on IoT for water quality monitoring.

In Figure 3, there are five major clusters, which are presented as green, blue, yellow, red, and purple. The clusters denote how strong is the connection is between the keywords in the published papers. The green cluster represents the "internet of things". The cluster was revealed to be strongly connected with "wireless sensor networks", "agriculture", "smart agriculture", "smart irrigation", and "energy efficiency." The "energy efficiency" in the green cluster indicates that the energy management issue is of high priority in the design of the IoT for water systems. The blue cluster represents "water quality monitoring". The cluster was revealed to be strongly related to "dissolved oxygen", "pH", and "temperature". The blue cluster also contains "aquaculture", "wi-fi", "wireless sensor network", "data handling", etc. The yellow cluster is also strongly connected to "water quality monitoring", and is related to the use of "lora", "wsn", and "low-power electronics". The red cluster represents "environmental monitoring", which is linked with the use of "machine learning", "artificial intelligence", "neural networks", and "wide area networks". The purple cluster is represented by "water supply", which is strongly related to "water treatment", "smart city", and network security". Note that the clusters are strongly linked with the "internet of things". This indicates that the "internet of things" has been the major focus of the published papers on environmental monitoring, water quality monitoring, water treatment, water supply, smart agriculture, and smart irrigation over the last decade. This consequently implies that the use of the "internet of things" is a leading area of research for addressing water challenges. In addition, the cluster analysis in Figure 3 similarly confirms that majority of research topics within the period of 2012 and 2022 centers on using "internet of things" for smart application monitoring.

The timeline analysis presented in Figure 4 shows a visualization of how keywords are mapped onto the color-coded timespan of the research that was conducted between 2012 and 2022. The keyword timeline analysis of the collected papers on IoT for water quality monitoring is shown in Figure 4. Figure 4 also illustrates the changes in the direction of research focus within this period. This shows that more studies in this timeline focus on the use of wide area networks for water quality monitoring purposes.

During the third step, we reviewed and analyzed the collected works. According to our results, research on how to address the problem of water loss, comprehensive studies on the research progress of water quality sensing networks, on how to improve water quality monitoring, and on water quality prediction, are common, while research addressing the resource management challenges associated with the use of IoT for water quality monitoring is less common.

2.3. Comprehensive Review and Analysis of the Collected Related Research

Paepae et al. [43] conducted a comprehensive survey on the use of IoT for water quality monitoring, especially for monitoring groundwater and surface water sources for irrigation use. The author discussed the important water quality parameters, such as *E. coli*, boron, electrical conductivity, dissolved oxygen, chemical oxygen demand, and pH, for irrigation water. The work also considered the use of machine learning with the IoT and the current progress of the use of virtual sensing for the assessment of irrigation water quality. However, the work did not consider how to address the various resource management challenges that are associated with the use of IoT and machine learning for water quality monitoring and prediction purposes. Similar to the work presented in [43], in Wagle et al. [44], the authors considered a comprehensive review of the use of different types of machine learning algorithms, such as the support vector machine, decision tree, and artificial neural network, for the assessment of the collected remote IoT water datasets. This work also addressed the resource management issues in the use of IoT for water quality monitoring.

Ahansal et al. [45] conducted a comprehensive study on the use of IoT, unmanned aerial vehicles, and machine learning to monitor and predict the water status of crops, and also to manage the use of water for smart irrigation. The IoT sensors used for acquiring the water level data from the crops are resource-constrained devices, while the use of machine learning for analyzing and predicting crop water status is also computationally resource demanding in terms of computational power and computational time. However, the work did not consider the resource management challenges in IoT and machine learning for smart irrigation. Without this, it is impractical to achieve a sustainable IoT and machine learning systems for smart irrigation.

Chen et al. [46] presented a comprehensive review of the studies that used artificial neural networks to develop water quality prediction models for several water quality parameters, such as biochemical oxygen demand, dissolved oxygen, chlorophyll a, temperature, arsenic, and coliform. The water data (or samples) used to build the models were collected by the IoT sensors deployed in various water bodies, such as lakes, rivers, and reservoirs. The work also reviewed the advantages and the disadvantages of the models in the literature. The use of artificial neural networks in IoT for water quality monitoring and prediction purposes requires computational resources, such as computational power and computational time. Additionally, artificial neural networks require high computations to predict water quality. However, the work did not consider the resource management challenges associated with the use of IoT and artificial neural networks for water quality monitoring.

Ighalo et al. [47] presented a comprehensive review on the use of IoT for the monitoring and assessment of water quality. The work also reviewed the research progress of IoWT networks. Their discussion on the research progress includes the application of IoWT to assess water quality, the issues related to software and hardware design, a review of some existing water quality monitoring systems, and an evaluation on the use of IoWT technology to assess water quality. The work discussed some of the microcontroller modules (e.g., Raspberry Pi) and the IoT communication technology modules (e.g., LoRA) used in IoT for water quality monitoring systems. However, there was no discussion on how to manage the resource utilization of these modules, especially in terms of power resources. In Ighalo et al. [48], the authors also presented a systematic review of the works that used artificial intelligence and the IoT water dataset to develop water quality monitoring and assessment models for surface water. Artificial intelligence models are highly computational-resource-demanding. However, there was no consideration on how to address the resource management challenges related the use of artificial intelligence and IoT for the monitoring and assessment of surface water quality.

Akhter et al. [49] presented a review of the IoT-based water quality monitoring for monitoring the acceptable limit of the essential water quality parameters for fisheries using various types of sensors, such as nitrite and nitrate sensors, pH sensor, temperature sensor, magnesium sensor, calcium sensor, phosphorus sensor, and dissolved oxygen sensor. This helps farmers to maintain a safe water quality for the marine fisheries to preserve their lives and to increase food production. The existing sensors for measuring various fisheries-based water quality parameters were also reviewed to identify their benefits and disadvantages. Moreover, the work proposed an IoT system for smart fisheries. However, the study did not consider any resource management strategy to address the resource management challenges that are related to the use of IoT for smart fisheries.

In Jan et al. [1], the authors presented a comprehensive study of the use of IoT for smart water quality monitoring for various domestic applications, such as drinking water and aquaculture water. The work reviewed some of the available water quality sensors and the IoT-based water quality monitoring systems for the monitoring of water used for domestic purposes. The work also discussed some the machine learning algorithms that are used in the field of IoT for water quality monitoring and assessment purposes. Moreover, the work identified some of the components in water quality sensors that consume a significant amount of power during operations. However, no solution is provided on how to address the scarce power, time, and bandwidth resources in IoT for water quality monitoring systems.

Kamaruidzaman and Rahmat [50] presented a brief survey on embedding the IoWT in water industry. The primary focus of the paper was the use of IoWT to address the water issues related to water monitoring systems, for example, water leakages, water quality monitoring, and water flow. In [51], the authors also presented the use of IoWT technology for the distributed monitoring of water systems to manage water loss as well as the distribution of water resources for various consumption purposes. However, these works have not considered the resource management challenges associated with the IoWT systems.

None of the reviewed studies above have addressed the resource management problems that currently hinder the sustainability of the IoT for water quality monitoring systems. Additionally, none of the studies have considered the use of game theory methods for solving power, bandwidth, and time resource management problems. To complement the limited power resources of the IoT sensors, some studies have exploited the use of energy harvesting technology for energy resource management and the use of optimization methods to manage the usage of the scarce power, time, and bandwidth resources.

In Virk et al. [52], the authors conducted a comprehensive review of different energy harvesting techniques that can be used to complement the powering of the water sensors deployed in water distribution systems. Such techniques include the use of radio frequency, thermoelectric generators, and solar, wind, and hydro generators. The work did not consider how other resource management challenges (e.g., time and bandwidth) in IoT for water quality monitoring can be addressed.

In [29], we studied how the energy resource management problem in water quality sensing networks can be addressed. We conducted a comprehensive review of several types of energy harvesting technologies that can be integrated into water quality sensing networks. The paper classified the discussed energy harvesting technologies into ambient and intended categories. Their classification on ambient energy harvesting technologies focused on energy solutions that harvest energy freely from the environment, for example, solar, wind, radio frequency, etc. The classification on intended energy harvesting technologies considered energy solutions that harvest energy from dedicated energy sources, including radio frequency. The paper also presented various types of conventional optimization methods for solving energy, time, and bandwidth resource management problems. The classification of the optimization methods includes custom optimization technique, meta-heuristic optimization techniques, linear programming techniques, soft computing methods, and geometric programming.

However, none of these studies have considered the use of game theory methods for solving power, bandwidth, and time resource management problems in water networks. Additionally, a comprehensive review of the integration and challenges of the use of game theory methods in water networks does not exist, to the authors' best knowledge. Hence, to fill the research gap in the field of IoT for water quality monitoring, this study presents a critical review of the use of relevant game theory methods for addressing the resource management challenges associated with IoT for water quality monitoring.

3. Overview of Water Quality Parameters and IoWT

3.1. Water Quality Parameters

Water quality parameters are indicators that are used to determine water quality. Examples include pH, dissolved oxygen, and temperature. The levels of water quality parameters are used to determine the fitness of water use for different applications. Water use can be categorized into several categories, including water use for agriculture (e.g., irrigation, aquaculture, and food production), industrial (e.g., materials and goods manufacturing), recreation (e.g., swimming), and domestic (e.g., drinking and cooking) purposes. These categories of water use have acceptable and/or safe levels of water quality parameters for safety reasons. As an example, high-quality river water that is fit for crop irrigation use may be unsuitable for municipal use or as drinking water for cattle, except when such river water is treated for the necessary removal of sediments [33,53]. Similarly, good-quality groundwater that is suitable for human consumption could be corrosive if used as marine fisheries water, except when the water is treated for corrosion [33,54]. Therefore, to certify water use for different purposes, the expected level of water quality parameters need to be satisfied. Hence, this section discusses some of the commonly monitored water parameters in agriculture; for instance, using IoT based on the bibliometric and comprehensive analyses carried out in this study. Examples are pH, turbidity, dissolved oxygen, temperature, electrical conductivity, and biochemical oxygen demand. As an example, in aquaculture water, the pH, dissolved oxygen, and dissolved carbon dioxide are essential parameters that may impact the survival, growth, reproduction, and respiration of the fish; hence, a safe level of these parameters needs to be maintained [55], otherwise poor water quality will result into an inferior fish produce with low profit and health risks for humans. For instance, the pH level of aquaculture water can impact the health of the fish in several ways, a pH level less than 4.0 can lead to acid-induced death, a pH level between 4.0 and 5.0 can result in a non-productive fishery, pH levels between 6.5 and 9.0 are desirable for fish production, a pH level between 9.0 and 11.0 can result in slower development of the fish, while a pH level greater than 11.0 can cause alkaline-induced death to the fish. The dissolved carbon dioxide concentration is an important parameter that is monitored in marine fisheries water using IoT since it affects the pH level of aquaculture water. Furthermore, the dissolved oxygen level of aquaculture water is another important factor that is monitored with IoT to ensure a safe oxygen level for the fish. For example, most fish cannot survive in water with low oxygen levels as this may cause them to suffocate [56]. Hence, keeping the water quality parameters within safe limits is important for healthy and productive fisheries. In a similar manner, a safe level of pH, turbidity, dissolved oxygen, temperature, electrical conductivity, and biochemical oxygen demand is needed for irrigation water for plant survival, growth, reproduction, and respiration.

3.2. Overview of IoWT

The IoWT is an appealing technology for addressing water challenges. It enables water quality monitoring networks to collect, compute, and transmit water data by connecting several smart devices (e.g., water quality sensors and actuators) through the internet to make the devices and their data accessible anytime, anywhere [11], as illustrated in Figure 5.

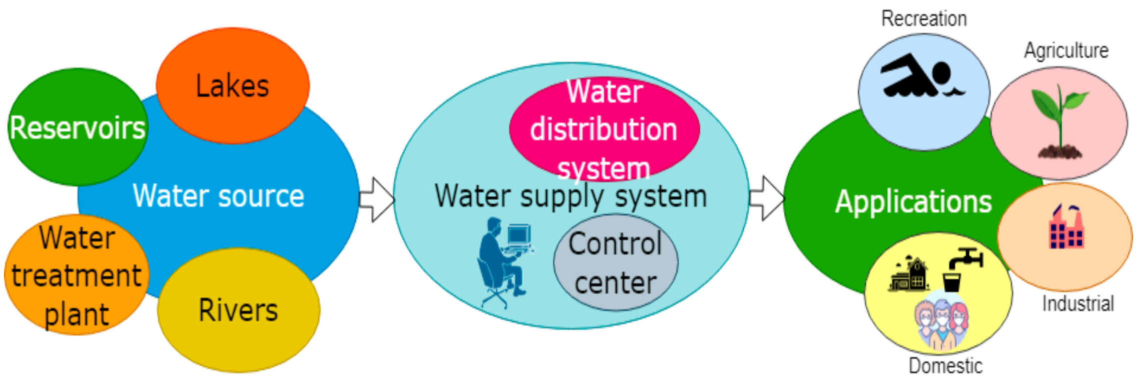

Figure 5. A typical illustration of an IoWT network [51].

The use of IoT technology is vital to everyday human activities, such as environmental monitoring, agriculture, healthcare, traffic monitoring, and home monitoring [57,58]. For example, in the water quality monitoring domain, IoT technology could assist to efficiently monitor changes in water quality, control the distribution of clean water for various consumption uses, and to guarantee the safety of the public health.

The water quality sensors in the IoWT networks are typically small in size. As a result, they only have space to accommodate small batteries with limited battery power, standard radios with a limited bandwidth for wireless communication channels, and processors with a limited processing speed [58–61]. These limitations have made the study of resource management an essential research focus for the IoWT networks to efficiently manage the limited resources (e.g., power, bandwidth, time) and to improve the network performance.

4. Examples of Optimization Methods Applied to Resource Management Challenges Arising in Water Quality Sensing Networks

Optimization methods are powerful operation research tools for developing resource management techniques used to solve resource management problems in water quality sensing networks. The common examples of such methods are based on heuristic programming and meta-heuristic programming. These methods, their applications, and their advantages and disadvantages in the realm of wireless quality sensing networks, are briefly reviewed in this section.

4.1. Meta-Heuristic Optimization Methods

Meta-heuristic optimization methods combine computational intelligence paradigms, such as swarm intelligence and evolutionary algorithms. In the realm of wireless networks, they may be applied to various types of optimization problems. Often, resource management problems in wireless networks are non-linear, and the consequential convex programming methods are not easy to apply. As a result, meta-heuristic optimization methods, which are suitable for most optimization problems in practice, are often sought to solve resource management problems related to wireless networks. Near-optimal solutions are often obtained in this way.

The approach involves adapting the standard meta-heuristic optimization methods (such as PSO, GAs, ACO, etc.) to several resource management problems arising in wireless networks. Examples are included in [62–64]. These studies adapted meta-heuristic optimization methods to wireless networks to address different resource management problems (such as time, power, and bandwidth), and to also improve various network performance (such as throughput and energy efficiency).

This approach may be adapted for most resource management optimization problems in wireless networks, and it often works well for the resource management problem it is applied to. However, solutions obtained using this approach are only near optimal. Moreover, in practice, meta-heuristic-based algorithms are computationally costly and complex as they incur more timing overhead during operation, especially when a large number of water quality sensors are considered. Unfortunately, the IoWT networks may not tolerate the delay due to the timing overhead, as such networks require real-time processing of water data.

4.2. Heuristic Optimization Methods

Heuristics are problem-specific approaches that are often sought to seek solutions to complex resource management problems in wireless networks when other optimization techniques do not fit. This type of optimization approach is developed based on the principle of logical ideas or rules of logic depending on the resource management problem that is formulated. Examples of studies that have exploited this approach are provided in [64–66]. These studies have addressed several resource management problems related to power and bandwidth.

This approach is useful to obtain resource management solutions with reduced computational complexity. However, most of the solutions that are obtained through heuristic algorithms are only suboptimal. Due to this, in the event of any increase in the size or dimensionality of a resource management problem, the quality of the solutions obtained is likely to diminish. Considering the heterogeneous and dynamic nature of the IoWT networks, heuristic algorithms may not be suitable for handling these properties. As a result, methods that are adaptive and strategic are more desirable for the IoWT networks.

4.3. Summary of the Optimization Methods Applied to Resource Management Challenges Arising in Water Quality Sensing Networks

A summary of the studied optimization method is presented in Table 1 to compare different optimization methods based on the addressed resource allocation problem, objective function of the proposed networks, and the advantages and disadvantages of the proposed optimization-based solutions.

Table 1. Summary of resource management solutions based on optimization theory.

Ref.	Optimization Method	Resource Allocation	Objective	Advantages	Disadvantages	Year
[62]	Meta-heuristic algorithm	Energy harvesting time, Information transmission time	Maximize energy efficiency	Provides a near optimal solution, Easy to implement, Suitable for a large sized network	High computational complexity	2018
[63]	Meta-heuristic algorithm	Harvested energy, Energy harvesting time, Information transmission time	Maximize energy efficiency, Maximize throughput			2020
[64]	Meta-heuristic algorithm	Spectrum	Maximize energy efficiency			2020
[64]	Heuristic algorithm	Power	Minimize energy consumption	Low computational complexity, Provides a suboptimal solution, Suitable for a large sized network	Solutions are problem specific, May be difficult to numerically analyze	2020
[65]	Heuristic algorithm	Spectrum (e.g., channel scheduling)	Minimize communication cost			2020
[66]	Heuristic algorithm	Harvested energy, Spectrum (e.g., channel scheduling)	Maximize throughput			2019

5. Game Theory Methods for Resource Management Challenges in IoT-Enabled Water Quality Sensing Networks

Generally, most resource management challenges in water quality sensing networks are formulated as a resource allocation optimization problem. The commonly employed conventional optimization methods for solving resource optimization formulations often provide solutions that are considered to be non-optimal since most of the resource management issues formulated as resource allocation problems are non-convex in reality.

Additionally, most of the solutions obtained using the conventional optimization methods suffer from complexity issues related to time and practical implementation, as well as convergence issues. The conventionally obtained solutions are not produced in real-time in many situations. Furthermore, due to the lack of proper mathematical modeling of the propagation environment, and other factors in defining water network management issues as resource allocation problems, it may be impossible to sufficiently formulate an optimization problem mathematically. Motivated by the aforementioned limitations, a more strategic optimization approach is considered in this study to address the resource management challenges of the IoT systems deployed for water quality sensing using game theory methods.

Game theory is an interesting alternative approach that could be employed to compute an optimal or near-optimal solution of non-convex resource management formulations for water quality sensing networks. To achieve this, game theory methods could be employed to model the behavior of water quality sensors as rational agents to optimize their gains. They can be used to achieve a distributed resource allocation among a set of resource competitors (i.e., water quality sensors), making it a powerful tool that could be applied to solving resource management challenges in water networks.

Game theory methods are mathematical optimization frameworks that combine the concept of optimization and computational methods to solve the decision-making problems related to the optimal control of network resources, such as time, bandwidth, and power in IoWT [67].

The theory of games has been successfully applied to several wireless network resource management issues related to power optimization. Examples are presented in [68–70]. These works employed game theory to solve the power management problem in wireless powered networks to determine the optimal power splitting of the harvested power to support energy harvesting and information processing, and to maximize their networks' gains. Game theory was applied to achieve this by modeling and analyzing the interaction among various participants in various game models.

Game theory methods have also been widely employed in economics, wireless communication, and politics [67] to meet the objective of determining the best solution or strategy for improving the performance gain of the individual players in a game. In games, each decision-making water quality sensor aims to optimize its decisions to maximize its own profit (reward or objective function). Therefore, each of the water quality sensors operates in a strategic environment where a participator tries to know the decisions (or intentions) of the others to make an optimal (or best) decision. For ease of understanding the operation of game theory, its mathematical descriptions and concepts are provided in the following sub-sections.

5.1. Fundamentals of Game Theory

A game G. could be described as an optimization framework, containing a principal and a 3-tuple: $\langle \boldsymbol{K}\,,\ \{a_k\}_{k=1}^{K}\,,\ \{r_k(\cdot)\}_{k=1}^{K}\rangle$, where the principal performs the role of setting the fundamental rules of the game; $\boldsymbol{K}$ denotes a set of players, $\boldsymbol{K} = \{1,\ 2, \ldots, K\}$; a_k is a set of actions (strategies or decision variables) represented as a vector $a = \{a_{1,}\ a_{2,}\ \cdots,\ a_K\}^T$ available to each water quality sensor k, such that each water quality sensor k makes a decision $a_k \in a$ for $k = 1,\ 2, \ldots, K$ to maximize its utility value (or objective function value) r_k, within the objective functions of all water quality sensors K based on the decisions they take in $r = (r_{1,}\, r_{2,}\ \cdots,\ r_K)$. The symbol, $(\cdot)$, denotes the expected value of each water quality sensor k, and $r_k(\cdot)$ eventually denotes the objective function value of water quality sensor k.

Consequently, r_k assigns an objective function value to each water quality sensor k based on the decision made, such that r_k: $a \to \mathbb{R}$ is the objective function value that is assigned to a water quality sensor k, resulting from the decision it made from the decision variable set a, where $\mathbb{R}$ is a real number. Hence, once a water quality sensor k makes a decision from $a = \{a_{1,}\ a_{2,}\ \cdots,\ a_K\}^T$, then the objective function that the water quality sensor realizes is dependent on $r_k(a_{1,}\, a_{2,}\ \cdots,\ a_K)$. Note that the objective function for all water quality sensors K (i.e., $k = 1, 2, \ldots, K$) is the Cartesian product (i.e., $\times$) of all water quality sensor decisions, i.e., $a = a_1 \times a_2 \times \cdots \times a_K$.

Based on the above knowledge of game theory, the modeling of a power allocation game framework to optimize the power requirements of the water quality sensor devices in a water quality sensing network could be given as $\langle \boldsymbol{K},\ \{a_k\}_{k=1}^{K}\,,\ \{r_k(\cdot)\}_{k=1}^{K}\rangle$, where the principal is the base station (BS), $\boldsymbol{K}$ is the set of water quality sensors (i.e., $\boldsymbol{K} = \{1,\ 2, \ldots, K\}$), a_k is the set of decisions or decision space (i.e., $a = \{a_{1,}\ a_{2,}\ \cdots,\ a_K\}^T$) of a water quality sensor k, and r_k could be used to compute the objective function value of each water quality sensor k based on the network constraints (e.g., throughput or data rate). Note, the decision space of each water quality sensor k could be used to define the set of the available power.

5.2. Concepts of Game Theory

5.2.1. Principal and Player

The principal is an element of a water quality sensing network that defines the rules of a game and provides the network resources to the players in a water quality sensing application. Specifically, the principal is a network controller (e.g., the BS).

As mentioned earlier, a water quality sensor is a decision maker in a game model. The water quality sensors are the network elements that receive shared and/or scarce resources (e.g., power, bandwidth, time) from the BS, and spends the acquired resources carrying out their primary tasks (e.g., sensing and transmitting) to achieve their individual goals and/or the overall goal(s) of the network. A water quality sensor in a game model is therefore a network element that has the ability to make a decision from the set of alternatives available to it as a decision, action, or strategy space.

In game theory, a game may be modeled such that all the water quality sensors make decisions at the same time. This type of game model is a simultaneous game. In addition, the water quality sensors of a game may be modeled to make decisions one after another to form a sequential game. The choice of decision-making approach is subject to the network requirement(s) and the objective(s) to be optimized.

5.2.2. Decision Variables, Constraints on Resources, and Strategies

A decision variable is used to determine the amount of resources (e.g., power) to be allocated to each water quality sensor in water quality sensing networks to calculate the value of the objective function (e.g., energy efficiency) of the network. To obtain an optimal value of the objective function, an optimal value of the resource allocation decision (i.e., decision variable) must be determined or computed.

Furthermore, to represent a real-life situation, constraints are set by the BS on the QoS or transmission parameters (e.g., power and time) to limit the way a resource could be allocated, and to satisfy the QoS requirements (e.g., throughput rates) of the water quality sensors.

In game theory, a decision variable is controlled by strategies. Basically, there are two types of strategies that govern how the network devices make a decision. They are pure strategy and mixed strategy [67].

A pure strategy is a rule that informs each water quality sensor of the specific decision to take from the available set of decisions. When a pure strategy is applied, a water quality sensor is expected to make a single decision from the available decision space.

In a mixed strategy, each water quality sensor makes a random decision from the available set of decisions based on some probabilities, involving $0 < i < 1$, where i is a probability parameter. An example is a power resource allocation game where there are heterogeneous water quality sensors, $\boldsymbol{K}$, that have different throughput rate requirements, and are expected to make a decision on the choice of transmit power based on the rate requirements. To achieve this, each water quality sensor, k, can choose a transmit power level using a mixed strategy based on probabilities defined by a vector $p = \{p_{1,}\ \ p_{2,}\ \cdots,\ \overline{p}_k\}^T$, such that $0\ \le\ p_k \le\ \overline{p}_k,\ \forall_k$, where p_k and $\overline{p}_k$ define the lower and upper bounds of each water quality sensor k transmission, respectively. Hence, each water quality sensor k can randomly make a decision from the power allocation set to satisfy the throughput rate in each measurement cycle. A mixed strategy uses more than one strategy by employing a probability distribution to enable the water quality sensors to randomly make a choice.

5.2.3. Utility or Objective Function

In game theory, the process of setting up a utility function is similar to that of the objective function in a conventional optimization problem. In the conventional optimization objective, the agenda is to optimize the objective function, and so it is in game theory. A utility function is used in game theory to compute the outcome of a game and is employed to practically model the objective of a network. For example, if the interest of a water network deployed for water quality monitoring is to improve network lifetime, then the objective function of the game model may be defined for network lifetime. Furthermore, any suitable game theory method could be employed to compute the objective function value.

5.2.4. Cooperative and Non-Cooperative Games

Generally, games are classified into two categories, namely cooperative games and non-cooperative games [71]. In a cooperative game, there exists a set of water quality sensors that have agreed to work collectively, with the aim of maximizing their overall objective function values. This type of game involves enforcing an agreement. To do this, a cooperative policy is used to introduce a binding agreement or a coalition between the water quality sensors, and this enables them to always cooperate to make decisions together by negotiating how to allocate resources. No agreement exists between the water quality sensors in a non-cooperative game, and they may consequently defect.

A cooperative game theory is applied when there exists a set of water quality sensors that have a common interest to be optimized, while a non-cooperative game theory is applied when there exists a set of water quality sensors, and each water quality sensor has its own individual interest to maximize.

In games, the concept of equilibrium is used to determine an optimal solution. Therefore, to analyze the equilibrium point of cooperative and non-cooperative game models, different types of equilibrium solution concepts are used as control policies or control laws to process the information available at the BS, and subsequently to determine the optimal values of the decision variables to obtain an optimal value of the objective function. Such information may be obtained via the network channels. The determined optimal values are used to produce control signals, which may be used to control the allocation of the network resources by the BS. The equilibrium solution strategy concepts are used to establish that the strategies played by the water quality sensors converge to a point of equilibrium, which in turn determines the value of the objective function obtained, and this value represents the network performance. The type of equilibrium solution concept applied has an impact on the network performance (i.e., optimal or near-optimal).

In cooperative game theory, the Nash bargaining solution (NBS) is an example of the available cooperative solution strategies, while the Nash equilibrium (NE) and Stackelberg equilibrium (SE) are examples of the solution strategies typically employed in non-cooperative games. Briefly, the NBS encourages a set of water quality sensors to cooperate and bargain to strictly play the NBS strategy, which forms a basis for computing and improving their objective function values. The NE makes sure that only the water quality sensors that stick to playing the NE decisions receive objective function values. Any water quality sensor that deviates from using the provided NE strategies obtains no objective function value, but obtains a reward or penalty as an objective function value. The NE concept is not considered as an efficient solution because of fairness, stability, and efficiency problems, which may not guarantee the Pareto optimal attained in a cooperative game model [71].

Examples of game models suitable for water quality sensing applications under the cooperative and non-cooperative games are coalition games, repeated games, bargaining games, potential games, and Stackelberg games [72,73]. Thus, the type of game model to use for solving resource management problems in water quality sensing networks depends on two key factors that determine whether the water quality sensors are cooperative or not cooperative; hence, if cooperative, a cooperative game model may be employed, otherwise, a non-cooperative game can be applied. Moreover, both cooperative and non-cooperative game theory may be used for modeling as well as analyzing the resource allocation strategies developed for the heterogeneous water quality sensors in a resource management problem.

5.3. Mathematical Formulation of Non-Cooperative Game Theory

Regarding the application of a non-cooperative game theory to a water quality sensing network, consider the definition of a non-cooperative game for a transmission rate control problem for water network data traffic, where $\boldsymbol{K} = \{1,\ 2, \ldots, K\}$ denotes a set of water quality sensors (i.e., players), vector a represents the transmission rates of all the water quality sensors, such that $a = \{a_{1,}\ a_{2,}\ \cdots,\ a_K\}^T$ is the set of transmission rate strategies available to each water quality sensor k, a_k represents the transmission rate strategy of each water quality sensor k, the throughput rate requirement for each water quality sensor k data traffic is modeled as $\vartheta_k(a)$, and the objective function value for each of the water quality sensors K is modeled in (1) as:

$$r_k(a_k\ ,\ \ a_{-k}\ ) = \omega_k\ \vartheta_k(a) - c_k\ a_k \tag{1}$$

where a_{-k} represents the transmission rates of all the water quality sensors apart from water quality sensor k, ω_k denotes the weight of the data throughput, and c_k is the transmission rate cost.

Furthermore, to describe the application of the NE strategy concept, the transmission rate NE solution of the given non-cooperative game can be defined as a set of strategies, $\boldsymbol{a}_{\boldsymbol{k}}^{*}$ for $k = 1, 2, \ldots, K$, such that no water quality sensor increases its objective function value as a result of selecting a different transmission rate, except if that selection complies with the transmission rates of the other water quality sensors, given by $\boldsymbol{a}_{-\boldsymbol{k}}^{*}$. Therefore, the NE solution of the non-cooperative game given in relation to the objective function of the game in (1) can be mathematically represented in (2) as:

$$r_k\left(\boldsymbol{a}_{\boldsymbol{k}}^{*},\ \boldsymbol{a}_{-\boldsymbol{k}}^{*}\right) \geq r_k(a_k,\ a_{-k}) \rightarrow \forall_k \in \boldsymbol{K} \tag{2}$$

The NE of each water quality sensor k can be computed from its best response. Note, the best response of each water quality sensor k defines its set of optimal strategies, and can be numerically computed in (3) as:

$$\boldsymbol{a}_{\boldsymbol{k}}^{*} = \mathcal{B}_k(a_{-k}) = arg \max_{a_k} r_k(a_k,\ a_{-k}) \tag{3}$$

To compute the NE solution, the difference between the solution strategy of water quality sensor k (i.e., a_k) and its best response $\mathcal{B}_k(a_{-k})$ can be minimized as an optimization problem in (4):

$$\min \sum\nolimits_{\boldsymbol{k}=\boldsymbol{1}}^{\boldsymbol{K}} |a_k - \mathcal{B}_k(a_{-k})| \tag{4}$$

From (4), the NE of the solution can be found at a point where the optimization problem (i.e., the objective function) tends to zero.

Note that the total objective function of each of the water quality sensors may be maximized if the water quality sensors cooperate as a centralized network, where a centralized decision-making policy is employed. Therefore, the total objective function of such a scenario can be formulated in (5) as:

$$\Im(a) = \sum\nolimits_{\boldsymbol{k}=\boldsymbol{1}}^{\boldsymbol{K}} r_k(a_k,\ a_{-k}) \tag{5}$$

To obtain an optimal strategy for the total objective function expression in (5) using a numerical method, an optimization problem may be modeled in (6) as:

$$a^{*} = arg \max_{a} \Im(a) \tag{6}$$

6. Examples of Game Theory Methods

In this section, some examples of the game theory methods that can be applied to solve resource management problems in water quality sensing networks are discussed.

6.1. Potential Game Theory

This type of game theory is an example of a non-cooperative game theory that could be applied to water quality sensing applications to optimize water quality sensor power requirement, throughput, and data transmission delay [74]. To achieve this, a potential game could be used to model the interactions among several water quality sensors in water quality sensing applications by formulating resource management problems as potential games.

Potential games are associated with a special element known as a potential function. The potential functions are used to map the action space a to a real number $\mathbb{R}$, that is, $a \rightarrow \mathbb{R}$, to compute the objective functions of the water quality sensors. The potential functions are also useful for tracking the changes in the objective function of the water quality sensor owing to their unilateral deviations [74].

Potential games may be mathematically formulated in different ways, such as exact potential games, weighted potential games, ordinal potential games, and generalized ordinal potential games, based on the relationship that is defined between the potential function and the objective function of a water quality sensor [74–82]. In potential games, the concept of the NE solution strategy could be used to model how the water quality sensors make decisions, and to determine their solution. The theory of potential game has been applied to resource management problems in IoT networks in the literature.

In [83], the optimization of the throughput requirements of device-to-device (D2D) communication was presented to increase throughput and reduce power consumption. In this work, the potential game theory was employed to formulate the interactions among the transmission paths as a power adjustment potential game. Additionally, an objective function was designed to evaluate the gain of each device. The objective function of each device was proven to be an ordinal potential function, while the power adjustment potential game proved to be an ordinal potential game. In [84], the theory of potential game was also applied to formulate the problem of power allocation as a potential game. The ideas presented in [83,84] could be applied to the IoWT system to improve on the usage of power, bandwidth, and time resources.

In [85], the channel management problem was studied to support the data transmission delay requirements of different smart devices in 5G networks to improve their QoS performance. The potential game theory was applied to model a transmission delay potential game for the devices. Furthermore, a potential function, which is an approximation of the objective function, was designed for the game. The transmission delay potential game proved to be an exact potential game, and its NE solution was proven to be a near-optimal solution. This idea could be adapted to the IoWT system to address its resource management challenges related to power, bandwidth, and time.

The potential game is a promising game theory method that could be applied to water quality sensing to formulate power, bandwidth, and time resource management problems to optimize the power requirements of water quality sensors, increase their throughputs, and reduce their data transmission delays. However, to apply a potential game theory to water quality sensing applications resource management problems, the existence of a potential function needs to be established for resource management formulations to be developed as potential games for power, bandwidth, and time resource management. In addition, the stability of the optimality of the potential game methods may not be guaranteed, as the available strategy in potential games may allow a water quality sensor to deviate from the pre-defined or formulated interactions. Hence, the solutions to water quality sensing applications resource management problems formulated as potential games are most likely near-optimal.

6.2. Repeated Game Theory

A repeated game could be employed to formulate power, bandwidth, and time resource management problems in water networks for water quality monitoring applications. This model allows a stage game to be played several times in a cooperative manner. Such a repeated game may have a final period or no end period. When a repeated game has a final period, it is referred to as a finitely repeated game, otherwise, it is an infinitely repeated game [86].

A finitely repeated game is played many times, and is bound to a fixed number of repeats by $\in \{1,\ T\}$; in contrast, an infinitely repeated game is played for an infinite number of repeats, with $t\ \in \{1,\ \infty\}$. In a finitely repeated game, K water quality sensors independently play a static game (i.e., a stage game), and select decisions simultaneously. Additionally, the final objective function value of each individual water quality sensor k is calculated by adding together the objective function values that each individual water quality sensor k received in each round t of a game, defined by $1 \leq t \leq T$, where T is the fixed (maximum) number of repeats.

For example, suppose a game is to be repeatedly played three times, hence $T = 3$. The outcome of the game that supposedly represents network lifetime performance is calculated based on the overall sum of each water quality sensor's objective function value in every period t for $t = 1,\ 2,\ 3$. Therefore, in each round t of a finitely repeated game, a water quality sensor k receives a total objective function $p_k \in (p_1, p_2, \cdots, p_K)$ for $k = 1, 2, \ldots, K$, and is modeled in (7) as:

$$P_k(\sigma) = \sum_{t=1}^{T} p_k\left(\varphi^t(\sigma)\right) \text{ for } k = 1, 2, \ldots, K \quad (7)$$

where $\sigma = (\sigma_1, \sigma_2, \cdots, \sigma_K)$ is the joint strategy the water quality sensors chose in each round t of the game, while $\varphi^t(\sigma)$ is the history of the strategy in each round $t \in \{1, T\}$.

In an infinitely repeated game, there exists a set of $\boldsymbol{K} = \{1, 2, \ldots, K\}$ water quality sensors that independently play a static game, and make decisions simultaneously. The final objective function value of each water quality sensor k is the infinite sum of all the received objective function values in each round t of a game defined by $t = 1, 2, \ldots, \infty$. Furthermore, an infinitely repeated game possesses the history of the strategies in each round $t \in \{1, \infty\}$, and has a discount factor of $0 < \propto < 1$ (i.e., $\propto \in \{0, 1\}$). Therefore, in each round t of an infinitely repeated game, a water quality sensor k receives a total objective function $p_k \in (p_1, p_2, \cdots, p_K)$ for $k = 1, 2, \ldots, K$, and is formulated in (8) as:

$$P_k(\sigma) = (1 - \propto) \sum_{t=1}^{\infty} \propto^{t-1} p_k\left(\varphi^t(\sigma)\right) \text{ for } k = 1, 2, \ldots, K \quad (8)$$

Repeated games provide an opportunity to induce cooperation, and also to keep the interactions of the water quality sensors as non-cooperative, thus, addressing the NE inefficiency in non-cooperative games in terms of selfishness.

In repeated games, common types of strategies that could be used to model how the water quality sensors make decisions can be classified into two types, namely static strategies and dynamic strategies. Examples of static strategies are to always defect, to always cooperate, and to randomly cooperate or defect. Examples of dynamic strategies are cartel, trigger (or Grim), tit-for-tat, and forgiving [51,67,87–89].

Repeated game formulations for solving resource management problems in water quality sensing applications are promising to optimize the power requirements of water quality sensors, increase their throughputs, and reduce their data transmission delays. However, the stability of the optimality of the repeated game methods for water quality sensing applications may not be guaranteed, as some of the available strategies in repeated games may permit water quality sensors to defect with punishment. Such a defection means that a solution strategy may be overridden by another strategy, making the available solution strategies in repeated games unstable. Hence, resource management challenges in water quality sensing networks modeled as repeated games may only provide a near-optimal performance.

Furthermore, in repeated games, the final objective function value of a water quality sensor is a function of the sum of all the objective function values received by a water quality sensor in each period t with $1 \leq t \leq T$ or $1 \leq t \leq \infty$ of the game. This process may potentially increase the complexity of repeated game algorithms due to the processing time. This limitation may overburden large water quality sensing networks. The limitations need to be efficiently addressed to apply this theory to resource management problems in water quality sensing networks.

The theory of repeated game has been applied to resource management problems in IoT networks in the literature. In [90], for example, a repeated game theory was employed to formulate a power control problem in wireless communication channels. In this study, wireless channels were modeled as players and a repeated game framework was developed to model the repeated interactions among different wireless channels. Each channel's decision space included the power cost for transmission and the signal-to-interference plus noise ratio (SINR) cost for channel service quality of the channel. The decisions available to each player were based on NE and the no-regret solution strategy concepts. For equilibrium analysis, the strategy concepts were analyzed to establish or prove the existence and uniqueness of the proposed power control repeated game model. The concept presented in [90] could be used to address the power resource management challenge in the IoWT systems.

6.3. Coalition Game Theory

This type of game theory is an example of a cooperative game theory, and could be used to model the interactions of a group of water quality sensors to manage power, bandwidth, and time resources. To form a coalition relationship among different players, two strategies may be employed, namely far-sighted strategy and myopic strategy.

When a far-sighted coalition game is formulated, water quality sensors choose their strategies through two means, i.e., learning from other water quality sensors and predicting the future strategies of other water quality sensors. Each water quality sensor in a far-sighted coalition game receives a long-term sum objective function value, a property shared with a repeated game, although it differs from a repeated game as it can use several types of strategies to punish any water quality sensor that defects an agreed solution strategy.

When a myopic strategy is used, the water quality sensors of such a game are allowed to adopt the strategies available to them in the current phase of the game in the next phase of the game alone, which continues over subsequent phases.

The solution strategies used by the water quality sensors of a far-sighted coalition game in their current states are dependent on the learned and predicted solution strategies of other water quality sensors in the previous states of the games, while the solution strategies used by the water quality sensors of a myopic coalition game in their new states depend on the previously used strategies in the former states.

When a game is formulated using the theory of a coalition game, solution strategy concepts, such as the nucleolus, the Shapley value, and the core are available, and could be potentially used to ensure the optimality of a game solution, unlike the case of a non-cooperative game that employs an NE solution strategy. Therefore, in coalition games, a central solution is implemented, and this contains the objective function value allocation set that encourages players to make decisions preferred by the group. Consequently, none of the water quality sensors from a specific coalition can improve its objective function value for deviating from its coalition. This solution ensures that no coalition of water quality sensors benefits from leaving its coalition to join another coalition.

Coalition game theory has been exploited in the literature to solve resource management problems in IoT networks, for example, in [91,92].

In [91], a coalition game theory was employed to formulate a power control and an interference mitigation problem in D2D communication. In this study, a coalition game framework was developed to model the coalition of D2D pairs to form a group of D2D users and to encourage them to increase their objective function, which is the sum rate, while minimizing transmission power and co-channel interference. The D2D pair coalition is a mutual agreement to share resource blocks (RBs). Each D2D pair coalition decision space includes the transmission power resource vector and RBs that are available for reuse/sharing. Different transmission power was computed and allocated to each D2D pair by the coalition game framework in connection with the assigned RBs used by a particular D2D link. Furthermore, to mitigate the effect of interference on the D2D pair communication, the allocation of transmission power is conducted in line with the interference onto the D2D pair during the allocation of an RB. The concept presented in [91] can be used to manage the power and bandwidth resources of an IoWT system in an interference environment.

The authors of [92] considered a power control problem in a wireless powered communication network. The agenda of this work was to individually maximize the objective function of each sensor device by determining the best value of the harvested power resource to be allocated in accordance with the signal-to-interference plus noise ratio (SINR) using the Shapley value solution strategy. For this purpose, a coalition game framework was developed to encourage the sensor devices in the system to work cooperatively to control their power and SINR, and to improve the individually received objective function. For equilibrium analysis, the Shapley value solution strategy was analyzed to prove the existence of the power control coalition game model. The Shapley value equilibrium solution strategy concept contributed to obtaining an optimal network performance. The work of [92] can also be applied to addressing power resource management challenges in the IoT for water quality monitoring systems.

The solution strategies (e.g., core and Shapley value) available in coalition games may be advantageous to improving the management of power, bandwidth, and time resources in water quality sensing applications compared to that of the NE solution strategy used in the non-cooperative games. Additionally, they may be helpful in improving the objective functions of the water quality sensors in coalition games. For example, a core solution strategy could not be overridden by another strategy, unlike in the NE solution strategy. The solution strategies of the coalition games may therefore contribute to stable resource management. Hence, resource management challenges in water quality sensing networks modeled as coalition games may provide optimal performance.

In addition, the use of a coalition game model for formulating power, bandwidth, and time resource management challenges in water quality sensing applications may contribute to improving fairness in resource allocation among different water quality sensors. This may help in optimizing the power requirements of water quality sensors, increasing their throughputs, and reducing their data transmission delays.

However, to obtain an efficient equilibrium among the water quality sensors, the interactions among them must first be analyzed. Due to the potential of large number of water quality sensors in water quality sensing applications, the required analysis may obviously lead to the exchange of large amounts of information. This process may increase the complexity of coalition game algorithms. Moreover, this type of game theory requires an agreement to be reached by the water quality sensors of each coalition regarding the solution strategy to be used, and how to compute their objective functions. This process may place some extra computation demands on each water quality sensor, and such computations may contribute to computational power and energy consumption. This aspect needs to be carefully dealt with to harness the benefits of coalition games in water quality sensing networks.

6.4. Bargaining Game Theory

This type of game theory is an example of a cooperative game theory that could be applied to solving power, bandwidth, and time resource management problems in water quality sensing networks by enabling two or more water quality sensors to come to an agreement to cooperate and negotiate on a solution strategy to maximize their total objective function [72].

A bargaining game is similar to a coalition game, as the water quality sensors in a bargaining game also cooperate; however, the concept behind their cooperation is different. For example, in coalition games, water quality sensors cooperate based a coalition of a set of water quality sensors, while the water quality sensors in a bargaining game cooperates based on the bargain they make to use a specific solution strategy.

The commonly used solution strategy concepts in a bargaining game are the NBS [93,94], the Egalitarian solution (ES), and the Kalai–Smorodinsky solution (KSS) [87]. The NBS is more popular because of its efficiency and fairness properties, since it is Pareto optimal. For instance, when the NBS is used, the water quality sensors in a bargaining game are compelled to use the strategies of the NBS. Based on the highlighted solution strategy concepts, bargaining games may obtain a near-optimal or an optimal network performance.

In a bargaining game, water quality sensors may be classified into clusters that contain no less than two water quality sensors. The water quality sensors in each cluster agree to collaborate, fairly share resources, and choose one of the available strategies (when multiple solution strategies are put in place) to improve the objective function of the cluster(s). Note that the water quality sensors that cooperate in a cluster have the potential to achieve a higher objective function value compared to the water quality sensors that do not cooperate.

The theory of bargaining game has been employed to address the power resource management problem in IoT networks, as, for example, in [95,96]. In [95], the authors formulated a power control bargaining game framework where radars are modeled as players.

The NBS equilibrium concept was employed to encourage the players to bargain and play the NBS strategy to control the allocation of transmit power. The decisions available to the players included a set of transmit powers. The objective function values of the radars were computed based on the NBS strategy. To analyze the fairness in transmit power allocation to the radars, the existence of the game was established. The idea presented in [95] is suitable for managing power resources in the IoT for water quality monitoring systems.

Based on the efficiency of the NBS bargaining game solution, the bargaining game model is a promising optimization framework that could be employed to address power, bandwidth, and time resource management challenges in water quality sensing applications. In addition, the bargaining game model may help to fairly share the network resources among the water quality sensors to optimize their power requirements, increase their throughputs, and reduce their data transmission delays.

However, bargaining game methods for power, bandwidth, and time resource management in water quality sensing applications may be limited by the bargaining process that the water quality sensors first make, which is resource demanding (e.g., processing time and computational power). As a result of this limitation, the bargaining game solutions to water quality sensing resource management formulations may be non-optimal for a large number of water quality sensors. The reason for this is that, as the complexity of these bargaining game models increases with the addition of more water quality sensors, the resource requirements of the models may also increase in terms of power and time.

6.5. Stackelberg Game Theory

This type of game theory combines the knowledge of both non-cooperative game and cooperative game theory to enable the water quality sensors in a Stackelberg game to select a solution strategy in a simultaneous manner (i.e., non-cooperative), while an additional principal IoT device, known as a leader, is involved in the decision making process, and acts in a sequential manner (i.e., cooperative). To apply this type of game theory to power, bandwidth, and time resource management in water quality sensing networks, the water quality sensors are modeled as followers, while the BS is modeled as a leader.

A Stackelberg game is an extension of the popular non-cooperative NE solution concept onto the SE solution concept, where the process of choosing a solution strategy is asymmetric. That is, the leader (i.e., the BS) dominates the process of decision making. The BS first chooses a solution strategy, and enforces it on the water quality sensors [97,98].

When this type of game is employed to formulate power, bandwidth, and time resource management challenges in water quality sensing applications, each water quality sensor chooses the best solution from a set of solution strategies announced to them by the BS. This type of resource management and decision problem requires a hierarchical SE model to enable the BS and the water quality sensors to be formulated in a hierarchical structure [97,98].

In this type of game, the role of the water quality sensors is symmetric, while the BS enforces its strategy on the water quality sensors. Before the BS announces its strategy to the water quality sensors, it first considers the possible responses of the water quality sensors, and decides on a favorable strategy for itself, the water quality sensors, and then enforces its decided strategy on the water quality sensors.

The SE strategy concept used in Stackelberg games prevents the water quality sensors of a non-cooperative game from deviating from the strategy announced to the water quality sensors by the BS as it chooses an SE solution, and ensures that the water quality sensors select a SE solution among themselves.

In the literature, the Stackelberg game theory has been applied to resource management problems in IoT networks, for instance, in [99,100].

In [99], the authors applied the Stackelberg game to a power allocation and interference management problem in small-cell networks to minimize power consumption, the co-tier and cross-tier interferences of small-cell user equipment (SUE), and the macrocell user equipment (MUE). In this study, a Stackelberg game framework was developed to model the MUE as the leader and the SUE as the follower. The SE concept was applied to determine the strategies to be engaged by the followers. Based on this strategy, the followers chose a transmit power from the power vector available in the decision space. This helped to avoid interference among the users during transmission. For equilibrium analysis, the existence of the SE was established to prove the optimality of the developed Stackelberg game. The solution of [99] can be applied to the IoWT system for power resource management.

In [100], the authors considered a power allocation and interference avoidance problem. A Stackelberg game framework was formulated to model an interferer water quality sensor as a follower, and a hybrid access point (HAP) device as a leader. An SE solution strategy concept was employed to enable the follower to observe the transmit power set by the HAP device to improve its objective function. Additionally, the HAP monitored the interferer level of the interferer device to improve its objective function. For equilibrium analysis, the existence of the proposed Stackelberg game was proven to show its optimality against the NE solution. This idea could be used to manage power resources in the IoWT systems.

The water quality sensors in Stackelberg games cannot deviate from playing the SE strategy announced to them by the BS because they operate under the control of the BS. Hence, this type of solution strategy guarantees an equilibrium, or an optimal point, of water quality sensing resource management formulations as Stackelberg games. Consequently, the Stackelberg game is an appealing optimization method for optimizing water quality sensor power requirements, increasing their throughputs, reducing their data transmission delays, and obtaining optimal solutions to water quality sensing resource management formulations.

Additionally, this type of game theory is suitable for improving water quality sensor performance (i.e., objective function values), as each water quality sensor in a Stackelberg game receives a higher objective function value when they use an SE solution compared to a water quality sensor that uses the NE strategy in non-cooperative games. Furthermore, the development of a Stackelberg game model for solving power, bandwidth, and time resource management challenges in water quality sensing networks may be advantageous to improve fairness in resource sharing among the water quality sensors in a water quality sensing network.

However, this type of game model suffers from a few constraints. For example, this game theory is more suitable for a resource management and decision problem with a hierarchical structure involving the modeling of the BS as a leader and the water quality sensors as followers. In addition, for the water quality sensors to select a solution strategy, the BS must first extract information from the water quality sensors individually to know their QoS requirements (e.g., throughput, power, and transmission delay requirements). Based on this, the BS sets a favorable solution strategy for itself and the water quality sensors. Consequently, this process may place a computational burden on the power-constrained water quality sensors in water quality sensing networks.

6.6. Summary of the Game Theory Methods Applied to Resouce Management Problems in Water Quality Sensing Networks

A summary of the studied game theory methods is presented in Table 2 to compare different game theory methods based on the addressed resource allocation problem, the objective function of the proposed networks, and the advantages and disadvantages of the proposed game-theory-based solutions.

Table 2. Summary of resource management solutions based on game theory.

Ref.	Game Theory Method	Resource Allocation	Objective	Advantages	Disadvantages	Year
[83]	Potential game	Power control	Maximize throughput, Minimize power consumption	Provides near-optimal resource allocation solutions (e.g., time, power, and channel) for IoWT	Lacks stability for optimality High computations, e.g., high computational power and high computational time	2018
[84]	Potential game	Transmit power	Minimize power consumption			2017
[85]	Potential game	Channel	Minimize transmission delay			2019
[90]	Repeated game	Power control	Maximize SINR	Provides near-optimal resource allocation solutions	Lacks stability for an optimal solution High computational time High computational power	2016
[91]	Coalition game	Transmit power	Maximize sum rate	Provides a low-complexity resource allocation Provides optimal resource allocation solutions for IoWT	Complex solution models Large number of variables	2020
[92]	Coalition game	Harvested power control	Maximize SINR			2018
[95]	Bargaining game	Transmit power	Minimize power consumption	Provides optimal resource allocation solutions for IoWT Provides a low-complexity resource allocation	Large number of variables Complex solution models	2018
[99]	Stackelberg game	Transmit power	Minimize power consumption	Provides a low-complexity resource allocation Provides optimal resource allocation solutions for IoWT	Complex solution models Large number of variables	2019
[100]	Stackelberg game	Power control	Maximize SINR			2016

7. Future Research Directions

To enable IoT-based water quality sensing networks to be functional, reliable, and sustainable, in this section, some major challenges that are associated with using game theory models to solve resource management problems in water quality sensing networks are discussed.

7.1. Information Exchange Overhead Challenge Associated with Game Theory Models for IoT-Enabled Water Quality Sensing Networks

Some of the game theory methods have the potential to experience overhead in the process of information exchange among the water quality sensors in water quality sensing networks. In practice, such overhead may be directly proportional to the number of water quality sensors. However, the water quality sensing networks may include a large number of water quality sensors, increasing the likelihood of delays due to information exchange.

The information exchange overhead may also impact the power, bandwidth, and time resources [101]. These issues need to be carefully addressed in formulations. The designs of efficient strategies then need to be taken into consideration and/or investigated when designing game models to reduce the power, bandwidth, and time resources associated with information exchange overhead by water quality sensors in the water quality sensing networks.

7.2. Addressing the Issue of Device Heterogeneity Related to NE Game Theory Models for IoT-Enabled Water Quality Sensing Networks

In some NE game models, the water quality sensors are mostly assumed to be homogeneous. Consequently, the water quality sensors are assumed to have similar requirements (e.g., throughput rates, power requirements, data transmission delay requirements). In practice, these may not represent a real-life situation, as the water quality sensors involved in water quality sensing networks may have different water quality sensors, different communication technologies, heterogeneous computational capabilities, and different behaviors.

As a result, to achieve efficient values of NE solutions to water quality sensing applications in the face of heterogeneous water quality sensors, the use of mixed equilibrium solution strategy concepts may be investigated to cater for the device heterogeneity. Additionally, the investigation and development of efficient distributed resource allocation learning algorithms is an appealing approach to obtain an equilibrium solution to the power, bandwidth, and time resource management challenges in water quality sensing networks formulated as games.

7.3. Addressing the Issue of Network Information Availability Related to Game Theory Models for IoT-Enabled Water Quality Sensing Networks

Most game theory algorithms developed for water quality sensing applications will use the CSI feedback from the BS to manage power, bandwidth, and time resources, and to optimize water quality sensors power requirements, throughputs, and data transmission delays. This may require the water quality sensors to request for the CSI from the BS. Consequently, the BS will compute the objective function of the resource allocation strategies.

Afterward, the BS broadcasts the strategies to the water quality sensors in the designed game model. This process requires the exchange of information among the BS and the water quality sensors for the CSI estimation at the BS [102]. Unfortunately, the CSI may experience some delay or distortion due to the wireless fading channel of the feedback channels from the BS and the noisy channels [103]. This situation may impact the availability of the CSI at the water quality sensors, hence, it may not be that easy to efficiently assign resources to the water quality sensors due to incomplete CSI information.

To address this challenge, techniques may be borrowed from machine learning to design game theory models for water quality sensing resource management formulations to enable the usage of offline CSI data to manage resource allocation when the CSI is unavailable as a result of delay or distortion.

7.4. Addressing the Behavioral Issue Associated with Game Theory Models for IoT-Enabled Water Quality Sensing Networks

To properly model the behavior of the water quality sensors in the water environment, realistic game models that include the behavior of such devices need to be developed. This will help to efficiently deal with the resource management challenges of water quality sensing networks, satisfy the power, throughput, and data transmission delay requirements of each heterogeneous water quality sensors, and improve the overall performance of the network. This is an active area of research.

7.5. Developing Machine Learning Methods for Game Theory Models for IoT-Enabled Water Quality Sensing Networks

In practice, there is no single game model that could be applied to solve all the resource management challenges arising in water quality sensing networks. To address this shortcoming, it will be interesting to investigate the integration of machine learning tools into water quality sensing resource management formulations as game models to enable such models to dynamically solve various water quality sensing and resource management problems.

8. Conclusions

This work presents a comprehensive review of the use of game theory for addressing the resource management challenges that are associated with the use of IoT for solving water challenges related to water quality monitoring. First, the relevant papers published over the last decade were collected from the SCOPUS database. Following this, we conducted a bibliometric analysis of the collected papers to understand the current research focus in the field. Subsequently, a comprehensive review of the publications was conducted to determine the existing research gaps. The review revealed that research on resource management in IoT for water quality monitoring applications is less common. Owing to the fact the IoT for water quality monitoring systems are inherently resource-constrained technologies, they require the investigation and development of novel resource management methods to make them sustainable in various applications, to extend their operation lifetime, and also to improve their data communication performance. To fill this research gap, we introduced the use of game theory on account of its advantages over other artificial intelligence methods (e.g., optimization techniques) in terms of computational complexity. Additionally, due to the lack of optimal solutions for most water quality sensing resource management formulations when using the conventional optimization methods, as such problems are mostly non-convex, we encourage, for the use of game theory, the methods in this paper to model and analyze the behaviors of individual or groups of water quality sensors in water networks. Moreover, the fundamentals of game theory methods are discussed, including their applications, strengths, and weaknesses. Furthermore, this study points out potential research directions and discusses the challenges to be addressed when developing game theory models for solving the resource management challenges of water quality sensing networks. In our future work, we plan to combine the use of another artificial intelligence method, specifically machine learning, with game theory to improve the learning and resource management performance of game-theory-based resource management methods developed for the IoWT.

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