EFFICIENT ENERGY RESOURCE MANAGEMENT FOR WATER QUALITY SENSOR NETWORKS

by

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SUMMARY

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Wireless sensor networks are promising technologies for the next generation of water quality monitoring (WQM) systems as a result of their appealing promises such as on-site measurements since some water quality (WQ) parameters are best measured at the water sites, low-cost, timely monitoring of WQ parameters, reliable delivery of WQ data to various WQM centres in remote locations, fast response rate, and early detection of water contaminations. For the promises of wireless sensor network to become a reality in WQM applications, various challenges that confront the performance of wireless sensor networks, such as energy problems including energy scarcity and consumption problems, and other resource constraints, are needed to be addressed. As a consequence, it becomes imperative to seek and develop viable solution models that can fairly and efficiently harness the limited

resources of wireless sensor networks among the network WQ sensors. This is essential for realizing the best for wireless sensor network in WQM.

To develop appropriate and viable solution models for wireless sensor networks, several issues which are barriers to achieving optimal solutions for the wireless sensor networks in WQM were identified and as well addressed in this thesis. Without this research efforts, the promises of wireless sensor network in WQM may not be realized. Thus, through a thorough study and analysis of relevant and useful works in the literature, crucial limiting factors to efficient resource utilization in wireless sensor network were identified and as well studied. This consequently led to studying and providing suitable solution models for addressing the limiting factors.

As a result of the inherent challenges, wireless sensor networks for WQM lacks what it takes to guarantee their sustainability and reliability in efficiently delivering WQ data to the designated remote water monitoring centres. Because of this limitations, the anticipated next generation wireless sensor networks for WQM are desired to possess greater capabilities to efficiently support sustainable network operations and reliable delivery of WQ data with optimal resource utilization. For this purposes to be achieved, it is essential for WQM sensor network systems to integrate pragmatic strategies for the provision of sufficient energy resources, judicious allocation and efficient use of energy resources. This research direction is targeted at bringing intelligent functionalities to the sensor network systems that are dedicated to the monitoring of WQ. These requirements have orchestrated a thorough technical study on how advanced methodologies such as radio frequency (RF) energy and optimization methods could be coupled with the WSN solutions for WQM applications to facilitate the realization of viable solutions with greater performance. As a consequence of the thorough technical study, this research has therefore proposed and implemented RF energy harvesting method and optimization strategies to tackle energy scarcity problem and efficient energy resource utilization issue. It is worth clarifying that energy resource provision and efficient energy resource utilization are crucial pivots upon which the productivity of wireless sensor network in WQM revolves. Consequently, this thesis has addressed the energy problems and provided viable solutions to the problems that challenge the fruitfulness of wireless sensor networks in WQM applications. The solutions offered by this thesis are not only viable, but are essential contributions designed to assist wireless sensor network to fulfil its asserted promises.

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To Jehovah.

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LIST OF ABBREVIATIONS

AC	Alternating current
ADC	Analog-to-digital converter
BS	Base station
CSI	Channel state information
CSMA	Carrier sense multiple access
CS	Carrier sensing
DC	Direct current power
DL	Downlink
DRFES	Dedicated RF energy source
E. coli	Escherichia coli
EH	Energy harvesting
HAP	Hybrid access point
Hg	Mercury
IPS	Intended RF power sources
IoT	Internet-of-Things
ISM	Industrial, scientific and medical
LP	Linear programming
LTE	Long term evolution
MAC	Medium access control
MCMIS	Multi-class, multiple-intended-source
MGMS	Multi-group, multi-source
MNMSMS	Multi-network, multi-sensor, and multi-source
OAERA	Optimization algorithm for efficient resource allocation

Pb	Lead
pH	Potential of hydrogen
PV	Photovoltaic
PHY	Physical
QoS	Quality-of-Service
RF	Radio frequency
SNR	Signal-to-noise ratio
SNMSMS	Single-network, multi-sensor, and multi-source
TDMA	Time division multiple access
UL	Uplink
WIPT	Wireless energy transmission and wireless information transmission
WSNs	Wireless sensor network
WPSN	Wireless powered sensor network
WPN	Wireless powered network
WQ	Water quality
WQM	Water quality monitoring
2G	Second generation of mobile network
3G	Third generation of mobile network
4G	Fourth generation of mobile network

LIST OF SYMBOL NOTATIONS

$a \in \{a_1, a_2, .., A\}$	Set of sensor nodes in Class A
$b \in \{b_1, b_2, .., B\}$	Set of sensor nodes in Class B
$c \in \{c_1, c_2, .., C\}$	Set of intended RF power sources
c_1 / g_1	Base station
D_{UL}	Effect of networks distance in the UL
E_a ; E_b	Total energy received by sensor *a ;* Total energy received by sensor *b*
$E\|.\|$	An expectation operator
$\|.\|$	Magnitude of an argument
ε_a ; ε_b	RF-to-DC conversion efficiency
$\tilde{m}_{c,a}$; $\tilde{g}_{c,b}$	Complex variable of Class A UL channels from sensor *a* to the BS ;
	Complex variable of Class B UL channels from sensor *b* to the BS
$\tilde{n}_{c,a}$; $\tilde{u}_{c,b}$	Complex variable of Class A DL channels from an IPS *c* to sensors *a*
	Complex variable of Class B DL channels from an IPS *c* to sensors *b*
Γ	SNR gap
j_c ; ζ_a	Time-length of Class A EH ;
	Time-length of Class A information transmission
J_{FI}	Jain's fairness index
k	Total number of sensor nodes *n* and *m*
ξ_0 ; ξ_b	Time-length of Class B EH ;
	Time-length of Class B information transmission
q_g^*, r_g^*	Optimal energy harvesting time
$m_{c,a}$; $n_{c,a}$	Class A channel power gain for UL channels ;
	Class A channel power gain for DL channels

$g_{c,b}$; $u_{c,b}$	Class B channel power gain for UL channels ;
	Class B channel power gain for DL channels
u	Summations of sensor nodes for Jain's fairness index
$R_u(\delta)$	Summation of the sum-throughput of Network 1 and Network 2
σ^2	Noise power
P_a ; P_b	Average energy consumed by sensor *a* for data transmission ;
	Average energy consumed by sensor *b* for data transmission
x_a ; x_b	Sensor *a* arbitrary random signal ; Sensor *b* arbitrary random signal
$x_{c_1,a}$; $x_{c_1,b}$	Signal received by the BS from sensor *a ;*
	Signal received by the BS from sensor *b*
$x_{c,a}$; $x_{c,b}$	Power signal received by senor *a ;* Power signal received by senor *b*
$x_{g,n}$; $x_{g,m}$	Received signal power at sensor nodes *n* and *m*
$x_{A,g}$	Arbitrary complex random signal from the dedicated RF power source
$\frac{1}{U}$; 1	Minimum fairness rate; Maximum fairness rate
Ψ_a ; Ψ_b	Fixed allowable portion of energy for sensor *a* data transmission ;
	Fixed allowable portion of energy for sensor *b* data transmission
z_a ; z_b	Background noise at sensor *a ;* Background noise at sensor *b*

TABLE OF CONTENTS

CHAPTER 1 INTRODUCTION

1.1 CHAPTER OVERVIEW

In an attempt to provide efficient systems for monitoring the quality of water due to the failure of the existing traditional laboratory-based systems which are bulky, costly, time-consuming, and inefficient, in this thesis, wireless sensor networks have been proposed as efficient monitoring systems. Furthermore, insights into critical issues are provided in this chapter, and the overview of each section in this chapter is provided as follows. Section 1.2 provides a preamble of the usefulness of quality water, the limitations of the existing laboratory-based methods, the need for novel sensing systems, and the dangers attached to poor water quality. Section 1.3 focusses on the research problem statement, Section 1.1.1 gives an insight into the context of the problem, and Section 1.3.2 identified the gap in research. Section 1.4 highlights the objectives of the research, and Section 1.5 dealt with the research hypothesis and approach. Section 1.6 enumerates the research contributions including the outputs. Section 1.7 presents the definition of important terms, and Section 1.8 gives the overview of the study.

1.2 PREAMBLE

In recent years, there has been effort by researchers to develop novel sensing systems for determining water quality (WQ) parameters such as pH values, dissolved metal ions (trace metals), and bacteria (E-coli), in a timely manner [1]. This is due to the increase in the influx of environmental and water pollutants [2] such as organic and inorganic contaminants, through anthropogenic activities and natural processes [3]. Consequently, water arising from these processes is harmful to public health due to the presence of micro-organisms and metal ions such as mercury (Hg) and lead (Pb). Moreover, these ions are environmental contaminants that create health issues such as cancer, organ damage, acute hepatic and renal failure, epigastric pain, and diarrhoea [4], [5], as well as environmental concerns at all levels due to their high toxic characteristics [6-8].

Water is indispensable and essential for human survival [9]. Therefore, clean water (as demanded by agriculture, industrial and drinking) is necessary for a good health and natural environment [10], [11]. Moreover, clean water is a valuable resource that needs to be monitored and maintained through efficient WQ systems. To address this technologically, a number of laboratory-based water quality monitoring (WQM) methods have been proposed, such as inductive-coupled plasma-mass spectrometry (ICP-MS), pH-metric determination optical-infrared spectroscopy, optical spectroscopy [12], [13]. The laboratory method requires water testing and analysis in water testing laboratories.

For instance, the Water Resource Commission No. TT 117/99 requires water sampling and analysis to be carried out by trained personnel using the laboratory-based methods in a laboratory environment to determine the chemical, microbiological and physical qualities of water such as dissolved metal ions, microorganisms, and pH [13], [14]. This implies that water samples are required to be taken to a laboratory for necessary analysis which requires days before getting responses [12]. This assessment process wastes a lot of time and cost.

The conventional laboratory-based methods are faced with other problems regarded as open research issues such as high cost, large size, difficulty in operating and deploying, requirement of off-site analysis, and interference from operators [15]. An efficient WQM system is characterized by parameters such as low-cost, low-power, and fast response time [11], [14].

It was reported in [16-20] that, the traditional method of taking water samples to the laboratory for assessment and characterization through conventional analytical techniques is no longer considered efficient.

Due to the shortcomings of the WQM approaches, and the risks environmental contaminants and water pollutants posed to human health, there is a need to develop efficient and novel systems to address the challenges of the conventional systems in a timely manner. As a result, research efforts are ongoing in the academics and industry to propose efficient methods for WQM [1], [21]. Also, to maintain quality water for the safety of lives, the World Health Organization (WHO), United States Environmental Protection Agency (USEPA), European Union (EU) guidelines [9], as well as the South African Department of Water and Sanitation [22], [23], are key reputable international bodies with indispensable contributions to the field of WQM. In order to meet the requirements of quality water provisioning in a timely manner to society as described by the aforementioned bodies, it is necessary to monitor and analyze water from different water stations in situ for contaminants for the purpose of drinking, as well as industrial and agriculture purposes, on a regular basis. To achieve this, an economical monitoring approach, called wireless sensor network technology, has been proposed through research efforts as a promising monitoring method.

Wireless sensor networks consist of either or both heterogeneous / homogeneous sensor nodes deployed in a geographical area of interest to monitor environmental physical properties, and sends the sensed data through either a single- or a multi-hop routing to a data sink node, and thereafter, the received data is forwarded by the data sink node through a communication network to a data centre [24], [25]. In the perspective of WQM applications, the promises of wireless sensor networks, especially the assurance of providing reliable monitoring of the parameters of WQ, have made them to gain intense attention and popularity over the years, as a suitable technology for WQM applications. Unfortunately, regardless of the promises of wireless sensor networks, there still exist open issues that may hinder it productivity in WQM applications. Examples of such issues include energy scarcity and energy consumption [26–32]. These issues can be attributed to the fact that the WQ sensor nodes in wireless sensor networks are battery-powered devices that drain their available limited energy during long operations when energy efficient strategies are not in place [25]. It therefore implies that, without the development of energy efficient strategies that can efficiently use the resources of wireless sensor networks which include energy resource, it will be impossible for wireless sensor networks in WQM applications to meet its ends. This difficult task therefore gives scope for further studies and motivates this research work. This thesis also focuses on identifying the key limitations of WNSs in WQM applications in terms of resource availability and finding optimal solutions to the limitations. To realize this, in this thesis, solution models are developed to tackle the shortcomings of WNSs in an attempt to make it more resourceful in WQM applications, as valuable contributions to the fields of WQM and wireless sensor network.

1.3 PROBLEM STATEMENT

Through the exploitation and exploration of wireless sensor network systems in WQM applications, there have been significant advancements in the monitoring of the quality of water. However, there are still issues that demands further investigation for the promises of wireless sensor networks in WQM applications to become a reality sooner. An example of such issue is the design of energy harvesting models for wireless sensor networks in WQM applications to address the problem of energy scarcity due to the finite energy of the batteries in WQ sensors because of their portable sizes. Consequently, WQ sensors can only accommodate tiny batteries. Unfortunately, the batteries used for powering WQ sensors do not have large energy capacity. Another problem is the design of energy resource allocation strategies to efficiently utilize the limited energy resource in wireless sensor networks. Energy is an indispensable resource upon which the activeness of the sensor nodes in a network is built. For example, a sensor node needs energy resource to carry out its key tasks that include WQ parameter(s) monitoring (or sensing), processing, and data communication. Typically, a sensor node is an energy-hungry device due to the energy dissipation of its components, especially the communication unit which employs a transceiver radio. As a consequence, the energy demands of the components of sensor nodes is traditionally large compared to the energy resource that is available in each sensor node in a network for continuously running its components. Hence, if energy efficient strategies for allocating resources are not devised, then it may not be possible for wireless sensor networks in WQM applications to meet their end goals. To address the issues raised, this thesis seeks answer to a number of research questions that include:

- Does the existing energy harvesting solutions for wireless communication systems apply to wireless sensor networks in WQM?
- What is the viable and sustainable energy harvesting source that can be employed as a power solution for a reliable network and efficiency?
- How can the identified energy solution be adapted to the wireless sensor networks in WQM?
- How can the energy scarcity problem in wireless sensor networks for WQM be addressed to guarantee energy sufficiency for a sustainable network operation?
- How can the energy consumption problem in wireless sensor networks for WQM be efficiently addressed and improved compared to the existing energy minimization schemes?
- What are the optimization approaches that will be applicable to solving the energy consumption problems in wireless sensor networks for WQM?

1.3.1 Context of the problem

Wireless sensor network has gained popularity in the field of WQM. Its popularity is as a result of its promises that include improving the process of monitoring the quality of water. Unfortunately, the long standing scarceness in resources has been a barrier to the effectiveness of wireless sensor networks in WQM applications. The scarceness of resources such as energy and bandwidth, used in achieving quality-of-service (QoS) have made it impossible to actualize energy efficiency, data rate, and reliability, in wireless sensor networks for WQM applications. Due to the varying QoS constraints imposed on wireless sensor networks, the limited resources in wireless sensor networks for WQM applications become worsened. To achieve the promises of wireless sensor networks, then it becomes crucial to develop and analyse efficient strategies to achieve the best from the little resources that are available, as well as complementing the available limited resources. These considerations are important to realize the possibilities of wireless sensor networks in WQM applications.

To address the energy scarcity problem in wireless sensor networks, there have been efforts in the aspect of devising strategies to complement the limited energy resource in wireless sensor networks through the exploitation of energy harvesting techniques. As energy harvesting is still a developing technology, more research efforts are required to be intensified to achieve a sustainable network operation. As a consequence, it is essential to critically study relevant energy harvesting models developed for wireless networks and wireless sensor networks for efficient adaption in solving energy scarcity problem in wireless sensor networks for WQM applications, as well as improving energy efficiency.

There have been little or no efforts in the area of energy resource allocation problem optimization in wireless sensor networks for WQM applications, as well as energy efficient WQ data communication. Due to the energy-hungry nature of sensor nodes, it becomes imperative to develop energy resource allocation models for optimizing the utilization of resources in wireless sensor networks. As a result, it is important to study related resource allocation models developed for solving the problem of resource allocation in wireless networks and wireless sensor networks to find optimal solutions to the resource allocation problem in wireless sensor networks for WQM applications, while the intricacies that are involved in wireless sensor network for WQM application are taken into consideration.

The development of energy harvesting models for seeking solutions to energy scarcity problem, and resource allocation optimization strategies for solving energy consumption problem in wireless sensor networks for WQM applications, are considered in this thesis.

1.3.2 Research gap

Currently, there are sizeable numbers of studies in the literature on wireless sensor networks for WQM applications. Based on the survey of the recent works on wireless sensor network for WQM carried out during this research, it is revealed that the solutions developed have omitted crucial aspects that would have advanced the field of wireless sensor networks for WQM applications. The existing works have not paid much attention to the aspect of energy consumption problem, especially due to data communication, and less attention has been given to the problem of energy scarcity. In a similar manner, most of the solutions in literature have not fully explored potential optimization techniques for seeking solutions to energy problems in wireless sensor networks for WQM applications due to the scarceness of resources. These inadequacies (or shortcomings) give scopes for research gaps in wireless sensor network for WQM applications. To address the identified inadequacies, this thesis focuses on the development of energy harvesting solution models for utilization in wireless sensor networks for WQM applications, as well as the development energy efficient resource allocation solution models that exploit optimization algorithms.

1.4 RESEARCH OBJECTIVE

This thesis achieved the following objectives during the research:

- Identification and investigation of critical problems that limit the application of wireless sensor network in WQM. The identified problems are barriers responsible for limiting wireless sensor network from realizing its end goals in WQM.

- Exploration of different energy harvesting techniques for solving energy scarcity problem in wireless sensor network for WQM and the incorporation of the energy problem in the developed models. The exploration of several energy harvesting techniques helped to identify and exploit a suitable and sustainable energy harvesting technique for realizing a sustainable network.

- Proposed the utilization of radio frequency (RF) energy harvesting in wireless sensor network solutions for WQM applications. The proposal of RF energy harvesting for powering WQM systems helped to achieve the realization of energy harvesting from a sustainable energy source for a sustainable network operation.

- Development of energy harvesting models for wireless sensor network in WQM that integrates the factors that limit the possibilities of wireless sensor network and address them. The developed energy harvesting models are used to provide solutions to energy scarcity problem and to guarantee energy efficiency in the network.

- Development of system models for solving resource allocation problem in wireless sensor network for WQM. The developed system models helped to study useful solutions to problems associated with resource allocation in wireless sensor network and are used to provide solutions to the limiting barriers that were identified.

- Exploration of different optimization strategies for seeking solutions to the problem of resource allocation in wireless sensor network for WQM. The exploration of several optimization strategies helped to efficiently exploit the problem structures of the system models to develop optimal solutions. For the purpose of validation, the solutions obtained to the developed system models through the exploitation of simulations and analysis are compared with the results of the state-of-the-art related works in the literature.

- Exploration of different enabling communication networks in wireless sensor network for WQM. The exploration of relevant communication networks for data communication in wireless sensor network for WQM helped to improve energy efficient communications.

- Exploration of different communication protocols (or technologies) and development of optimized communication protocols. The exploration of suitable communication protocols for providing access to the communication channel helped in developing new communication protocols that implement newly proposed optimization algorithms for energy efficient communications in the networks.

- Development of models that explore the concept of multi-networks and wireless information and power transfer (WIPT) for solving problems that hinder the realization of obtaining optimal solutions to resource allocation in wireless sensor network for WQM. The introduced concept helped to tackle the limiting effects of the identified barriers to the productivity of wireless sensor network, thus obtaining solutions that enhance the resourcefulness of wireless sensor network in WQM. The multi-network concept was also employed to seek solutions to the unfairness problem in resource allocation in a wireless powered sensor network.

- Development of models that explore the concept of network heterogeneity and wireless powered network (WPN) for addressing problems that limit the productivity of the application of wireless sensor network in WQM. The application of the concept helped to seek optimal solutions to problems that hinder the resourcefulness of wireless sensor network in WQM.

1.5 HYPOTHESIS AND APPROACH

In addressing the identified problems in this thesis, the research hypotheses are given as follows:

- The proposed energy harvesting schemes will provide efficient solutions to the scarcity of energy problem in wireless sensor network for WQM.

- The proposed energy optimization schemes will ensure energy efficient resource utilization and address high energy consumption problem in wireless sensor network for WQM.

- The proposed system models will guarantee energy sufficiency for a sustainable network operation.

This study has adopted a well-established process for a technical research in computer engineering, wireless networks, and wireless communications, with a special focus on wireless sensor networks. The stages involved in carrying out this research are therefore enumerated as follows:

- Literature study: This phase was the first aspect of the study and was devoted to the in-depth exploration of wireless sensor network, studying energy problems in comparison with other types of wireless sensor networks for opportunities and peculiarities purposes, studying energy harvesting techniques, studying optimization, and other key strategies that include multi-variate (or multi-network) and network heterogeneity.

- Design of system models: System or network models are crucial tools for seeking solutions to engineering problems. Several system models were developed in this research work to seek solutions to energy problems. To tackle the energy problems, the developed system models considered the identified limiting factors to the accomplishment of the end goals of wireless sensor network systems in WQM. As a consequence, the developed solution models incorporate strategies such as multi-networks and network heterogeneity to seek solutions to energy problems in wireless sensor network for WQM. The models were further analysed in a thorough manner and the obtained results are presented. The presented results are discussed in this thesis, in different chapters.

- Simulation of system models and numerical analysis: This phase was used to simulate the developed system models and to also perform numerical analysis. To achieve this, discrete-event simulation software such as C# programming and MATLAB were employed for this research work due to their various advantages such as user friendliness, availability of advanced functions suitable for the computation and processing of complex mathematical models, and ease of components integration with other languages.

- Validation of simulation results: In this phase, the validation of the results generated through the simulation processes using numerical analysis is carried out. Furthermore, results are validated and verified through comparative comparison with the results of the related existing state-of-the-art works in the literature.

1.6 RESEARCH CONTRIBUTIONS AND OUTPUTS

In the course of the research, several contributions were made to the body of knowledge on wireless sensor network in WQM as enumerated as follows:

- An in-depth study on wireless sensor network in WQM was carried out and the investigation revealed the barriers to the usefulness and productivity of wireless sensor network in WQM. Such barriers include energy constraint issues. The issues are limiting factors that are significantly crucial and stands as problems if not efficiently tackled. This work addressed the energy constraint issues to help wireless sensor network in WQM to achieve its promises of providing appealing, reliable, and sustainable solutions suitable for the effective, efficient, and timely monitoring of the quality of water to guarantee the safety of the public health.

- For the first time, this work will be the first to utilize RF energy as a sustainable power solution for powering wireless sensor networks deployed for WQM.

- Design and development of energy harvesting models to address energy scarcity problem in wireless sensor network for WQM.

- Design and development of optimization algorithms for solving high energy dissipation problem in wireless sensor networks deployed for WQM by developing energy resource utilization problem as an optimization problem.

- Design and development of efficient resource allocation schemes for solving the fundamental unfairness problem in wireless sensor network for WQM.

- Design and development of energy efficient communication protocols for optimizing network resources and to improve the efficiency in the communication system.

- Improve the throughput QoS requirement of wireless sensor network systems deployed for WQM to enhance the reliable transmission of WQ data with an efficient energy cost and also improve the response rate of response rate of WQ data communications.

- Improve the communication architecture of wireless sensor network in WQM for a low-cost WQ data networking.

- Development of heterogeneous-based multi-class and multiple resource wireless transmission wireless sensor network models that are most appropriate for WQM to satisfy network requirements and improve network efficiency.

The resulting contributions from this research have been published or accepted for publication in highly reputable peer reviewed journals in computer engineering, wireless networks, and wireless communications as full-length research articles. A publication list of articles that resulted from the research is enumerated as follows:

High-impact ISI rated peer reviewed journal articles:

1. S. O. Olatinwo and T.H. Joubert, "Energy efficient solutions in wireless sensor systems for water quality monitoring: a review," *IEEE Sensors Journal*, vol. 19, no. 5, pp. 1596-1625, Mar. 2019. (Journal Impact Factor: 2.617).

2. S. O. Olatinwo and T.H. Joubert, "Optimizing the energy and throughput of a water-quality monitoring system," *MDPI Sensors*, vol. 18, no. 4, p. 1198, Apr. 2018. (Journal Impact Factor: 2.677).

3. S. O. Olatinwo and T.H. Joubert, "Efficient energy resource utilization in a wireless sensor system for monitoring water quality," *EURASIP Journal on Wireless Communications and Networking*, https://doi.org/10.1186/s13638-018-1316-x. (Journal Impact Factor: 2.407).

4. S. O. Olatinwo and T.H. Joubert, "Enabling communication networks for water quality monitoring applications: a survey," *IEEE Access*, **(accepted).** (Journal Impact Factor: 3.557).

High-impact SCOPUS rated peer reviewed journal article:

1. S. O. Olatinwo and T.H. Joubert, "Maximizing the throughput and fairness of a water quality monitoring wireless sensor network system," *International Journal on Communications Antenna and Propagation*, vol. 8, no. 6, pp. 448-460, Dec. 2018 https://doi.org/10.15866/irecap.v8i6.15031.

1.7 DEFINITION OF TERMS

In this thesis, different terms were employed to describe several concepts associated to wireless sensor network in WQM. Examples of such terms are optimality, throughput, fairness, energy efficiency, and productivity, and are briefly defined as follows:

- Throughput: This term describes the overall amount of data transmitted by a wireless sensor network system per unit time. The overall amount of data simply implies the total data rate of all the network sensor nodes. Typically, throughput is measured using bits per seconds (or bits/seconds). In the perspective of wireless sensor network for WQM, throughput defines the total amount of WQ data the network can transmit.

- Optimality: This term describes the best result(s) that is/are obtainable in regards to the current conditions at which the wireless sensor network system devoted to the monitoring of the quality of water operates. In the perspective of wireless sensor network in WQM, the optimality of the wireless sensor network in WQM is said to be obtained if the best result(s) of the applied performance metrics, for example fairness rate and throughput rate are achieved, considering the currently available network resources and several network constraints.

- Fairness: This term describes the impartial distribution of the available network resources among the WQ sensors in a wireless sensor network system in order to ensure fair allocation of resources in the network. Note that the closer the fairness rate is to 1, the fairness the allocation of resources among the sensors in a network, and the higher the fairness rate value the better the performance of the network.

- Energy efficiency: This describes the energy utilization rate of a wireless sensor network system dedicated to the monitoring of WQ and its parameters.

- Productivity: The term simply describes the efficiency of a wireless sensor network system in association to its end goals.

1.8 OVERVIEW OF STUDY

The arrangement of the thesis structure is described as follows:

In Chapter 2, in-depth background knowledge is presented on the research work through a detailed and comprehensive survey on wireless sensor network for WQM. Chapter 2 addressed the relevant aspects of wireless sensor network in WQM including the recent works on the subject matter in the literature. Through the survey, the areas of wireless sensor network in WQM that have been well addressed were revealed, while the limiting barriers to the optimal productiveness and usefulness of several wireless sensor network solution models were as well uncovered. To seek solutions to the identified limiting barriers to the wireless sensor network systems, various solutions were analysed and this provides an essential direction in addressing the shortcomings of wireless sensor network in WQM. In Chapter 2, an exhaustive survey regarding energy efficient solutions for wireless sensor systems particularly for wireless sensor network in WQM was carried out. Examples of such solutions are energy harvesting models, energy optimization methods, and suitable wireless networks for WQ data communication including the presentation of new communication network architecture for wireless sensor network in WQM. The solution models that were presented considered the wireless sensor network for WQM requirements and as well takes into account the differences between other types of wireless sensor networks and the wireless sensor network for WQM.

Chapter 3 focuses on the development and analysis of models that address the problems of energy scarcity and energy consumption in wireless sensor network for WQM. Chapter 3 introduced the concept of multi-network and multi-energy-resource as an appealing strategy to seek solutions to the energy problems, which are long-standing barriers to wireless sensor networks. In Chapter 3, a fundamental doubly-near-far problem is encountered in the developed wireless sensor network for WQM. The identified problems are significant issues that confront the effectiveness of the wireless sensor networks in WQM applications. Through the exploration of the introduced concept, the energy problems and the doubly-near-far problem are effectively tackled. In Chapter 3, energy harvesting from dedicated RF energy sources are considered to address the scarceness in the availability of energy in the network, and optimization strategies are developed to efficiently utilize network energy resources as well as maximizing the overall achievable sum-throughput rate of the WQM system.

In Chapter 4, the concept of network heterogeneity is introduced to address the network requirements of the wireless sensor network for WQM, as well as to find optimal solution to the problems of energy scarcity, energy consumption, and resource allocation. To address the mentioned problems, optimal optimization methods are developed, and a new approach to energy harvesting and WQ data transmission optimization in a heterogeneous multi-class and multiple resource wireless transmission system that focusses on monitoring water and its quality is presented. Through the developed optimization methods, the sum-throughput of the WQM system is maximized to reduce the system energy consumption and enhance the system overall throughput rate.

In Chapter 5, the concept of multi-group and multi-source system is introduced to address energy problems and the unfairness issue in resource allocation among the WQ sensors in a wireless sensor network system for WQM. The aforementioned problems are great limiting barriers that hinder the resourcefulness of wireless sensor network in WQM. The newly introduced concept was employed to effectively seek holistic solutions to the problems. In Chapter 5, optimization strategies are employed to develop energy efficient solutions to maximize the fairness in energy harvesting and WQ information transmission throughput in the new multi-group wireless sensor network system devoted to the monitoring of WQ.

In Chapter 6, detailed discussions on the strategies proposed and developed for seeking solutions to the energy issues in wireless sensor network for WQM are presented.

In Chapter 7, the concluding remarks of the research work are presented, including the presentation of recommendations for future considerations on various aspects of wireless sensor network for WQM.

1.9 CHAPTER SUMMARY

The key essence of this chapter were to provide an insight into the shortcomings of the existing laboratory-based WQM systems which provides a context for the desire for efficient systems for monitoring the quality of water, including the provision of insights into critical issues in terms of the usefulness of quality water, and the dangers attached to contaminated water. This chapter has also provided the research problem statement, research gap, objectives of the research, research hypothesis and approach, research contributions and outputs, definition of terms, and the overview of the study.

CHAPTER 2 A REVIEW OF ENERGY EFFICIENT SOLUTIONS FOR WIRELESS SENSOR SYSTEMS IN WATER QUALITY MONITORING

2.1 CHAPTER OVERVIEW

In the quest for wireless sensor network to become a special type of indispensable wireless network in the monitoring of WQ and its parameters in the future, energy efficient solutions are paramount for wireless sensor network systems at water stations. This is critical because of the debilitating long-standing energy problems that challenge the productivity of WNSs. Consequently, critical issues are addressed in this chapter including the provision of energy efficient solutions, and the overview of each section in this chapter is provided as follows. In Section 2.2, the overview of wireless sensor network in water quality monitoring is presented. Section 2.3 focuses on the types of energy solution models that can be explored for a potential exploitation in WQM systems. In Section 2.4, a water quality sensor node that is equipped with energy harvesting technology is designed, and several types of optimization tools that could be maximized for solving energy consumption minimization problem in wireless sensor network systems for WQM are discussed in Section 2.5. In Section 2.6, several open research problems on the energy efficient strategies for wireless sensor network systems in WQM are presented, and Section 2.7 gives the summary of the chapter.

2.2 OVERVIEW OF WIRELESS SENSOR NETWORK IN WATER QUALITY MONITORING

Wireless sensor networks are key resourceful technologies that have revolutionized the field of environmental monitoring in recent years [33]. An important domain in the field of environmental monitoring is WQM. The term WQ is used to describe the physical, the chemical, and the microbiological characteristics of water, while the idea of sampling and analysing the characteristics of water on a periodic basis is described as WQM [34].

WQM systems can be realized in an efficient manner through the incorporation of wireless sensor technologies such as wireless sensor networks [27], [28]. Although the emphasis in this thesis is on WQM systems, the application of wireless sensor networks is not limited to only to this field, but is useful in several other domains such as water leakage monitoring [35], [36], waste management [37], [38], structural health monitoring [39–41], traffic monitoring [42–44], and farm animal condition [45], [46], to collect, process, and disseminate data to various data centers [47], [48]. Importantly, wireless sensor networks are valuable tools in WQM [1], [26–28], [47-49]. As an example, in [49], a WQM solution was deployed to monitor the salinity in ground water, and also to monitor the temperature of surface water, providing crucial details about the WQ status.

Wireless sensor network for WQM applications may contain a large number of WQ sensor nodes that have the capabilities to measure and detect the physical, chemical and microbiological parameters of water. An Escherichia coli (E. coli) bacteria is an example of a microbe that can be detected in water, while examples of chemical parameters that can be detected in water are heavy metals.

The incorporation of wireless sensor networks to WQM facilitates the effective monitoring of WQ parameters at water sites, as the WQ node in a network are devoted to the monitoring of WQ at a particular water site and disseminates their measurements to a data gathering station, which is referred to as a base station (or sink node) in practice. Similarly, wireless sensor networks are capable of transferring the measured water information at a local station to remote WQ centers through the application of communication network technologies such as the internet. As a result, a wireless sensor network based WQM system can effectively communicate with the remote end user devices in a timely fashion, enabling efficient monitoring of WQ parameters.

However, the WQ nodes contained in wireless sensor network for WQM applications have several resource constraints that range from communication capabilities, limited energy, processing capabilities, to limited memory for data storage [50], [51]. Among the aforementioned constraints in resources, energy is the most crucial resource of all [52]. The main reason for its high significance is that all components of a sensor node depend on it, as it is used for powering sensors. Energy limitation has been a long-standing issue in wireless sensor network applications [29], [53-55], while seeking solutions to the problem has been an active area of research in recent years. Typically, when there is a lack of energy in a network, one can say that there is an energy crisis in such network, which is technically referred to as energy scarcity. This is an indication that energy resource is a scarce commodity among the energy-hungry WQ node in wireless sensor networks. The energy scarcity problem in wireless sensor networks is a major issue that hinders the development and the continuous popularity of wireless sensor network applications [30-32].

The primary reason for the energy scarcity problem in wireless sensor network for WQMs is because the sensors that form a WQ node are based on battery power. As a result of the nature of WQ nodes, small batteries with finite energy are typically embedded in them. Because of the small size of the batteries, their energy budgets are restricted and are quickly depleted during sensors' operations, which include sensing, processing, and data communication. These operations determine the total energy consumed by each sensor node, which could be determined from the addition of the power dissipation of all the operational modules of a sensor node. These modules include all the sensors with their read-out front-ends, the micro-controller, and the RF radio. One the reasons responsible for the quick depletion of the energy in a sensor node's in-built battery during long operations can be associated with the embedded high energy consumption components - for example, the communication unit. Unfortunately, once any of the WQ nodes has exhausted the available energy in its in-built battery, its inactivation in the network compromises the data reliability.

Since wireless sensor networks have different applications and WQM is one of key use cases, it is important to underline the peculiarities of wireless sensor network systems for WQM applications in relation to energy problems. Typically, each application area of wireless sensor networks has different requirements in the context of measurements, and this determines the types of sensor modules in application sensor nodes. This disparity impacts the energy requirements of wireless sensor networks in different applications as energy consumption varies from sensor to sensor. For instance, the energy consumption of a temperature sensor in a WQM application differs from the energy requirements of a gas sensor in an air quality monitoring application as a gas sensor typically consumes more energy. The wireless sensor networks in different applications may also adopt different operation modes such as periodic data acquisition and continuous data acquisition. Periodic mode allows the network sensor nodes to be in a sleep state for a given time period, while a continuous mode requires the network sensor nodes to be active at all times. Another difference may be how often the sensor nodes in an application have to communicate their measurements. These differences create a disparity in energy consumption among different wireless sensor network systems as the power requirements of an application caters for peculiar features that include type of sensor module, operation mode, sampling rate of measurements, processing of the measured data, and rate of communication of measurements. Furthermore, in the case of wireless sensor network for WQM application, commercial low-power WQ nodes is currently not available, and this gives scope for the provision of energy-efficient solutions in wireless sensor network systems devoted to WQM applications since energy is a scarce resource. Other distinctive features of wireless sensor network systems for WQM applications are water sampling location(s) selection and number of WQ nodes required for optimum coverage, taking energy and cost into consideration. Taking the disparities among different application areas of wireless sensor networks into consideration, it is important to underline the need for energy-efficient solutions to address the peculiarities of wireless sensor network for WQM application regarding energy consumption problems so as to meet the requirements of wireless sensor network systems for WQM applications.

In order to meet the requirements of wireless sensor networks for WQM that include reliable and timely delivery of WQ information [56] through sustainable quality-of-service (QoS) for information transmission such as throughput rate [57], the economical exploitation of energy resource is crucial. Energy utilization efficiency is an example of wireless sensor network for WQM application requirements [57]. Consequently, the research community in industry and academia has been making efforts to address the energy problem in wireless sensor networks so as to improve the lifetime of wireless sensor network systems. Because of the current lingering energy problem in wireless sensor networks, it may not be possible to satisfy the requirements of wireless sensor network for WQM applications since sending a high volume of the measured WQ information in a timely fashion at a high throughput would consume more energy. To meet the aforementioned requirements of wireless sensor network for WQM systems and facilitate the successful and wide-spread deployment of their application, it is important to incorporate energy efficient strategies into wireless sensor network for WQM application designs.

Because of the growing interest in wireless sensor network systems, there are a sizeable number of surveys on wireless sensor networks in the literature. However, there are presently only a few of survey works on wireless sensor network for WQM systems in the literature. Examples of survey works that focus on wireless sensor network and WQM are discussed as follows. In [58], the authors presented the survey of wireless sensor network for WQM. In their survey, the authors emphasize key research problems in wireless sensor network for underground WQM application. Examples of the issues considered in their survey are deployment, architectural, protocol stack, and underwater communication. The authors in [59] considered the survey of wireless sensor network for WQM systems. Their survey work focuses on the recent developments which include communication models, WQ data acquisition, potential power models, and network architecture. The goal of this survey was to bring the awareness of the research community in wireless sensor network for WQM to recent advances, research issues, and possible solutions. The authors in [60] present a survey on wireless sensor network for WQ. Their goal was to highlight the key solution models to address the problem of water scarcity through the loss of water, which could be attributed to water leakages. Examples of such solution models include water leakage detection algorithms and localization approaches. The authors in [61] considered a survey on the exploration of smartphone technology in the framework of wireless sensor network systems for WQM. Reference [62] considered the survey of environmental monitoring applications such as WQ and air quality. In their survey, they focused more on the problems that relate to wireless sensor network for WQM. Examples of the issues considered by the authors are security, energy, coverage, and wireless sensor node architecture. The existing surveys have not considered the aspect of the energy consumption problem, and less attention has been given to the problem of energy scarcity. In a similar manner, none of the surveys in literature on wireless sensor network for WQM applications has considered potential optimization techniques for seeking solutions to energy problems. Different from the existing survey works on wireless sensor network for WQM, this work considers possible energy solution models and energy minimization inspired by optimization techniques. These are crucial design goals for sustainable energy supply and network communications in wireless sensor network for WQMs. To handle these energy problems, insight into the knowledge of different energy solutions and energy optimization models are important.

2.3 COMMON ENERGY SOLUTION MODELS IN WIRELESS SENSOR NETWORKS

Considering the energy problems that are associated with wireless sensor network systems that are powered by batteries, it is crucial to explore alternative energy sources for the realization of sustainable data communication and a reliable network. Thus, this section presents a review of some alternative energy solutions that could be harnessed to power the WQ node in wireless sensor network systems. Alternative energy solutions could be utilized to complement the usage of batteries. The alternative solutions can be classified into two basic categories based on ambient energy solutions, and intended energy solutions. These techniques are envisioned to mitigate the energy crisis in wireless systems [63-68]. For the purpose of clarity, a typical taxonomy of the energy harvesting solutions that are based on ambient and intended sources is given in Figure 2.1.

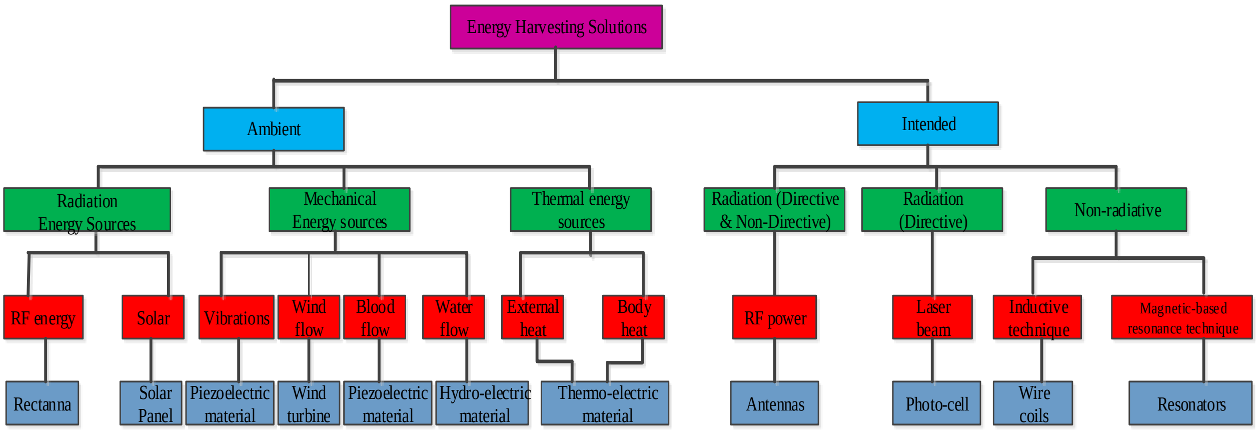

Figure 2.1. Taxonomy of a typical energy harvesting solutions based on ambient and intended sources.

2.3.1 Classification based on ambient energy solutions

In this subsection, we present a brief overview of energy harvesting solutions in wireless sensor networks that are based on ambient sources. Energy harvesting is concerned with the scavenging of energy from renewable energy sources. These types of energy are naturally occurring energy in the environment, and they are therefore freely available. Energy from these sources is green and likewise gives birth to green communication in wireless networks. To exploit the numerous benefits of renewable energy sources, energy harvesting systems are employed. It is worth clarifying that some energy harvesters operate as an AC source, while others are modelled as a DC source. The block diagrams of AC and DC energy harvesters are depicted in Figures 2.2 and 2.3, respectively. It is important to mention that the energy harvested through the reviewed energy harvesting techniques cannot be employed directly to power a sensor node, or to store energy directly in a battery device. As a consequence, they are subjected to power conditioning processes that involve AC rectification, and a DC-DC conversion.

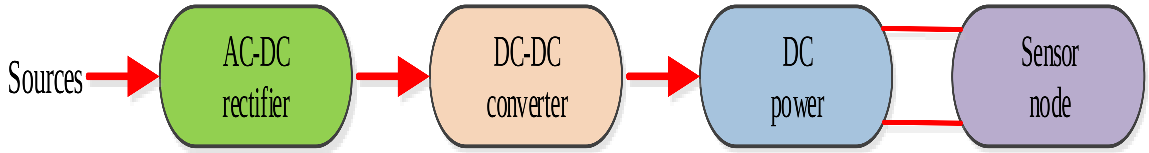

Figure 2.2. Energy harvester for AC source

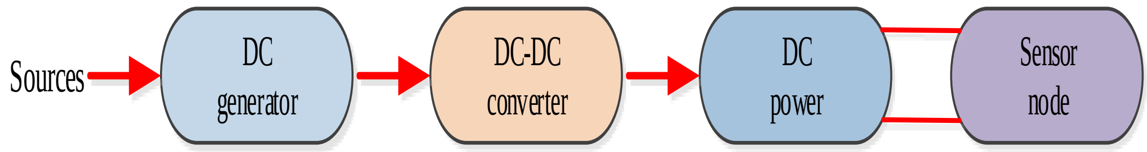

Figure 2.3. Energy harvester for DC source

An energy harvesting system can be described as an embedded system in wireless sensor networks, employed to address energy problems such as energy scarcity. It is composed of three basic components, namely an energy harvester, energy storage, and an energy management unit [69]. The energy harvester is employed to harvest energy from energy harvesting sources, and converts it into an electrical energy suitable for powering the sensor node components (sensing unit, processing unit, transceiver unit). Thereafter, the generated electrical energy is delivered to the energy management unit for further actions [70].

Several wireless sensor network solutions have been proposed using various types of energy harvesting techniques to harvest energy from different renewable energy sources. Energy harvesting sources can be classified into three basic categories, namely, radiation energy sources (RF waves, solar), mechanical energy sources (vibrations, wind, water flow, blood flow), and thermal energy sources (external heat, body heat). Examples of energy harvesting techniques are solar energy harvesting, thermal energy harvesting, vibration energy harvesting, and RF energy harvesting. A short overview of some of the energy harvesting techniques is presented below.

2.3.1.1 Vibrations energy harvesting

Energy can be generated from the vibrations produced by mechanical devices. These vibrations are sources of mechanical energy [71]. By employing a piezoelectric method, the mechanical energy obtained from vibrations can be converted into electrical energy [72], [73]. Vibrations energy harvesting are based on AC source as illustrated in Figure 2.2. A small number of vibration energy harvesters have been developed. Some examples of vibration harvesting systems for powering wireless sensor networks, and where they have been deployed, may be found in references [74-78].

This technique may be applied to wireless sensor networks devoted to the monitoring of WQ for powering the sensors in a network. For instance, the authors in [78] adopted a piezoelectric technique to harvest from a vibrational energy source to power a wireless sensor network system devoted to the monitoring of WQ. Due to the materials employed, the method has high energy efficiency of about 60% [79]. However, this method is confronted with an issue of charge leakage [80], which may be due to piezoelectric material deterioration. Figure 2.4 describes the block diagram of vibration energy harvesting.

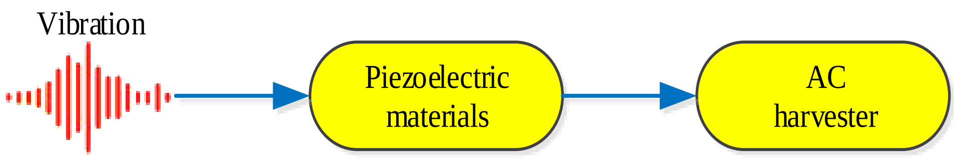

Figure 2.4. Diagrammatic representation of vibration energy harvesting

2.3.1.2 Thermal energy harvesting

This technique provides the opportunity to harvest energy from waste heat from sources that include friction, heaters, and furnaces. By exploiting thermal energy harvesting, energy can be harvested from thermal gradients, otherwise known as a temperature difference. Using a thermoelectric generator, thermal gradients can be converted into an electrical energy. This method is capable of harvesting thermal energy once a temperature difference is established, and is based on an AC source as illustrated in Figure 2.2. Conversely, this method is limited by the failure to maintain a temperature difference between two different metals, which also act as the conductive electrodes in the transducers. This technique is not a suitable candidate for powering WQ node, due to the low efficiency of the thermoelectric generators employed for harvesting thermal energy. The efficiency of the thermoelectric generators which is typically less than 11% is a function of the performance of the thermoelectric materials within them [81]. Technically, the efficiency of the thermoelectric generators can be enhanced to improve the output power and the voltage levels of the thermal energy harvesting system, by putting multiple thermo-electric materials in place. However, doing so would incur high cost, and also increasing the size of the energy harvesting system. This renders the method only suitable for large scale applications [78]. Some good examples of thermal energy harvesting systems can be found in references [82], [83]. For example, the authors in [83] exploited thermal energy harvesting method to harvest the waste heat from a thermoelectric system. Figure 2.5 describes the block diagram of a thermal energy harvesting.

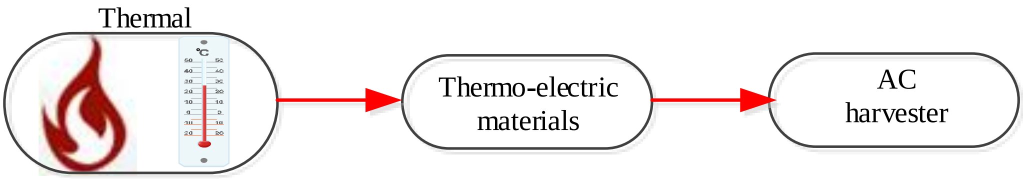

Figure 2.5. Diagrammatic representation of thermal energy harvesting.

2.3.1.3 Solar energy harvesting

Energy can be harvested from light produced by artificial means or by natural means. An example of an artificial light source is a man-made light, such as a torch, while an example of natural light is sunlight (solar). Using a photovoltaic method, the light obtained from the identified sources can be converted into electrical energy [71]. Solar energy harvesting solution models have been developed in [71], [84], [85]. For example, the authors in [86], [88], [151] have considered solar energy for powering wireless sensor network systems for monitoring WQ. In the cited references, different harvesting systems have been developed to harvest energy for light environments, either indoor or outdoor. This technique may be applied to wireless sensor networks devoted to the monitoring of WQ, to enhance the system viability. The efficiency of this method depends on the efficiency of the photovoltaic (or solar) cell type employed. Some examples of photovoltaic cells are thin-film, mono-crystalline, and poly-silicon. Note that the mono-crystalline type is commonly employed because of its high energy conversion efficiency which is typically less than 25%. Consequently, it is key to underline that this method has a low efficiency [89]. Furthermore, this method is limited when light is not available and also suffer from quick depletion [90]. Solar energy harvesting may support both AC and DC sources as illustrated in Figures 2.2 and 2.3 depending on the source of light. As an example, in the case of sunlight, an AC source is applicable, while a DC source is employed in the case of an artificial indoor light that is based on rechargeable cells. Figures 2.6 and 2.7 depict the block diagrams of solar energy harvesting from both natural and artificial energy harvesting.

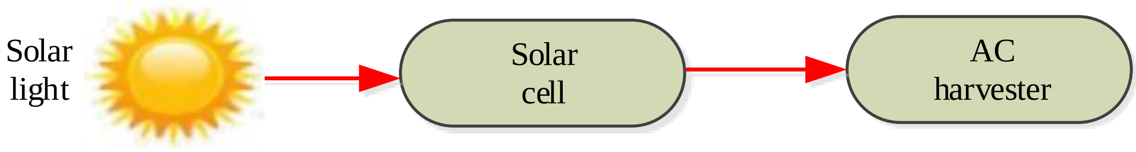

Figure 2.6. Diagrammatic representation of solar energy harvesting from natural light.

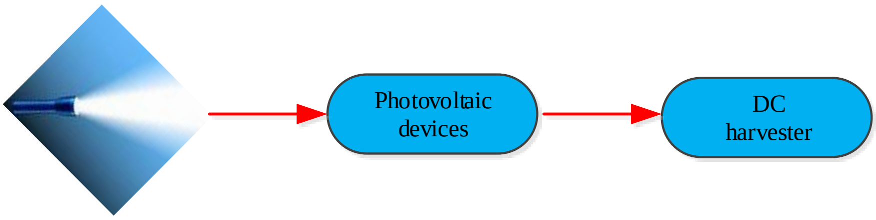

Figure 2.7. Diagrammatic representation of solar energy harvesting from artificial light.

2.3.1.4 Wind energy harvesting

Wind is also a potential source of energy that can be generated in large amounts in coastal areas. Energy can be harvested from the waves produced by wind or air. energy harvesting A wind energy harvesting system employs energy generators such as piezoelectric. Using a piezoelectric generator, a linear motion can be exploited from the blow or flow of wind, which is thereafter converted into electrical energy. Other generators employed for exploiting wind are triboelectric nano-generator, permanent magnet DC generator, series wound DC generator, and shunt wound DC generator [91]. The piezoelectric- and triboelectric nano-generators are based on an AC source, while the permanent magnet DC generator, series wound DC generator, and shunt wound DC generator are based on a DC source. A wind turbine for harvesting energy from wind may either exploit an AC source block or a DC source block as described in Figures 2.2 and 2.3 depending on the adopted generator. This technique may be combined with other methods and applied to wireless sensor networks dedicated to the monitoring of WQ, to enhance the lifetime of the system.

Unfortunately, wind energy harvesting is limited by fluctuations in the strength of the wind, low flow rates, low energy efficiency of about 38.28% [92], as the generators commonly employed in the exploitation of wind energy suffers from low conversion efficiency [81], and the unpredictable nature of flow sources [71]. Some examples and where they have been developed are found in references [93], [94]. For example, in [93], a wind energy conversion system was developed to power wireless sensor network applications. Figure 2.8 describes the block diagram of a wind energy harvesting.

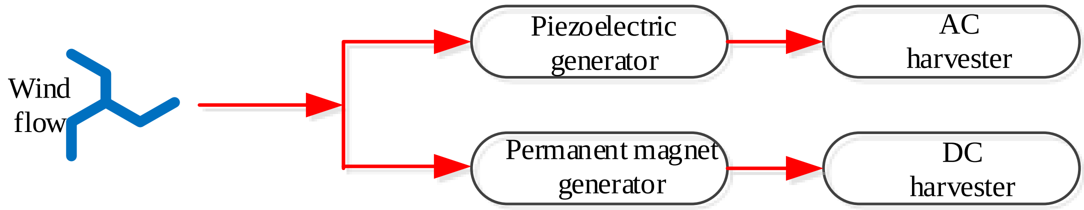

Figure 2.8. Diagrammatic representation of wind energy harvesting.

2.3.1.5 Water flow energy harvesting

This technique may be explored to harvest a small amount of energy from the flow of water. In this technique, kinetic energy is harvested from the water flowing through a pipe by integrating a hydro-electric (or a water turbine) system that is connected to a DC power generator such as a permanent magnet DC generator. Water energy harvesting is based on a DC source as depicted in Figure 2.3. This technique has been applied to wireless sensor networks for aquaculture and metering applications [95], [96]. Typically, it is more useful and employed in large scale applications, for example hydro-electric dams, where there is continuity in the re-circulation of the water flowing in water pipes. Otherwise, this technique suffers from uncontrollable energy generation when applied to wireless sensor network systems, like in the case of solar energy harvesting [95], [96]. For instance, energy harvesting from water is not possible when the flow of water is zero. Consequently, other techniques are required to make a wireless sensor network system operational. Without the integration with multiple methods that may include solar and wind, it will not be functional for powering the sensors in a network. For example, in [97], the authors considered harvesting from multiple energy sources that include water flow, solar, and wind for powering the sensors in their system. Due to some possible intermittent flow in water, the amount of energy harvested at a time may not measure up with the energy requirement of a particular wireless sensor network. Also, energy harvesting from water requires bulky systems and is complex [98]. Consequently, this technique is still impractical to power WQ node in wireless sensor network application. Furthermore, it is characterized by low energy efficiency of about 8% due to the low conversion efficiency of the generators used to exploit energy from the flow of water [81]. The block diagram of water energy harvesting is illustrated in Figure 2.9.

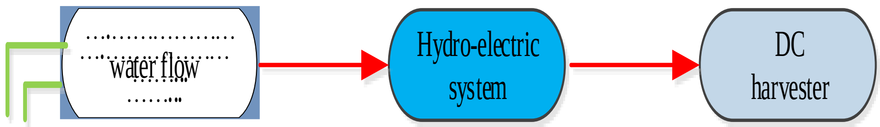

Figure 2.9. Diagrammatic representation of water energy harvesting.

2.3.1.6 Radio frequency energy harvesting

RF energy can be described as the radiation of electromagnetic (EM) waves. An electromagnetic wave or RF energy can be radiated in a frequency range of 3 kHz to about 300 GHz [90]. RF energy harvesting describes the process of scavenging energy from electromagnetic (RF) wave radiations. To achieve this, a rectifying antenna (rectenna) is employed to acquire and convert the RF waves from RF sources into electrical energy as described in Figure 2.10, while the AC block in Figure 2.2 is employed for necessary rectification for necessary rectification. However, when little beam shaping is applied, this method experiences low efficiency when the RF wave spreads omnidirectionally from the source.

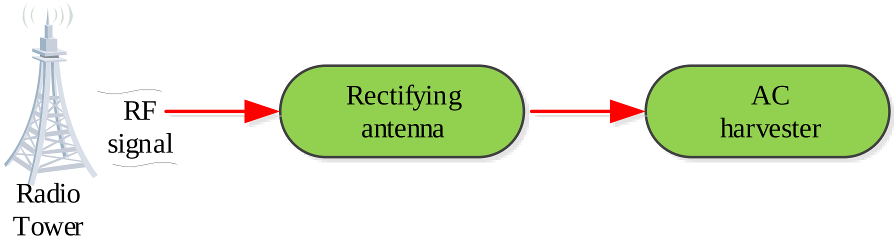

Figure 2.10. Diagrammatic representation of RF energy harvesting process.

RF energy sources can be categorized into two groups [99], namely ambient RF energy sources, and dedicated RF energy sources. Ambient-based RF sources are not primarily dedicated to the transfer of RF energy, but they are freely available for harvesting to energy harvesting devices such as energy harvesting WQ node. Consequently, their availability is not predictable. Also, the ambient-based method has low energy efficiency with an increasing transmission distance. Examples of ambient RF energy sources include television towers, radio towers, microwaves, Wi-Fi routers, and cell phones [71]. Dedicated RF energy sources are often employed for RF energy transfer in WQ node, where a predictable supply of energy is required. With dedicated RF energy sources, the sources are deployed and committed to the supply of RF energy to the WQ node at a pre-defined rate and frequency [99]. Furthermore, a dedicated RF energy source can transfer RF energy to the WQ node through the reserved ISM frequency bands. Thus, RF energy sources are controllable, and offer suitable QoS performance for wireless sensor network applications [99]. Some good examples of dedicated RF energy sources include the Powercaster transmitter [100], the Cota transmitter [101], and Isotropic RF transmitters [102]. In comparing a dedicated RF energy source with other energy sources that include ambient RF, wind, solar, water and vibrational sources, it has a number of advantageous characteristics [99], such as stable and predictable energy harvesting over a fixed distance.

In summary, various energy harvesting sources and techniques have been identified, and their strengths and drawbacks are highlighted. In order to make a wireless sensor network application sustainable, a suitable energy source should be considered along with the area of deployment of the wireless sensor network application. This simply implies that, as part of the design, the energy harvesting WQ node should be deployed in areas where the chosen energy source is densely available. Also, to meet the needs of a specific wireless sensor network application, two or more energy sources could be hybridized or combined to generate more – and more consistent - energy [69]. Furthermore, some of the energy harvesting sources are uncontrollable [90]. Based on their uncontrollable characteristics, they can be classified into various perspectives. Such classifications include [103] uncontrollable and unpredictable, uncontrollable but predictable, partially controllable, and fully controllable. Uncontrollable and unpredictable energy sources are energy sources that cannot be controlled or predicted to generate energy when desired. Uncontrollable but predictable energy sources are energy sources that cannot be harvested when desired, but their behavior can be modelled to determine when energy can be harvested. Partially controllable energy sources can be partially harvested at a desired time. Fully controllable energy sources can be harvested at any desired time. The behavior of this type of energy source is human-controlled. For comparison, a summary of the important reviewed methods is given in Table 2.1, containing solution approaches, harvesting technique, power density, efficiency, strength, drawbacks, and examples of application systems. The formulated Table would assist in making an optimal choice among the identified energy harvesting methods.

Table 2.1. Energy harvesting solutions to energy issues in wireless sensor network.

	Energy source	Solution approaches	Harvesting technique	Power Density	Strengths	Drawbacks	Applications	Refs
1.	Vibration	Electric energy is generated through piezoelectric material straining	Piezoelectric	Industrial: 100 µW/cm^2 (1m at 5 Hz) Human: 4 µW/cm^2 (0.5m at 1 Hz)	Predictable High efficiency	Stability issues, Uncontrollable, Unpredictable, Charge leakage	Train route tracking Event monitoring (sabotage activities) Train monitoring	[77] [104] [105] [106]
2.	Thermal	Temperature gradients are converted into electrical energy	Thermoelectric	Industrial: 10 mW/cm^2 Human: 25 µW/cm^2	Predictable	Uncontrollable Low efficiency	Industry (waste heat energy recovery), Micro-scale application	[82] [83] [107]

3.	Solar	Natural light (sunlight) or artificial light (touch light) is converted into electrical energy	Photovoltaic	Indoor: 0.01 W/cm^2, 100 μW/cm^3 Outdoor: 10 mW/cm^2, 100 mW/cm^3	Fully controllable (artificial light) Uncontrollab-le, but predictable (sunlight)	Intermittent Costly Bulky Light-dependent Low efficiency	Biomedical Wildlife	[69] [108] [85] [109]
4.	Wind	Wind wave linear motion is exploited and converted into electrical energy	Piezo-turbine Triboelectric	At a wind speed of 5 m/s: 380 μW/cm^3	Available at all times for harvesting no matter how little the flow could be	Uncontrollable Unpredictable Low efficiency May not be useful for some WSN and IoT systems	Water treatment Agriculture	[91] [94] [110]
5.	Water	Water flow is exploited through a hydro-electric (or a turbine) system that is connected to a DC power generator	Hydro-electric system Permanent magnet DC generator	At a flow velocity of 2 m/s: 16.2 μW/cm^3	Available for harvesting when there is continuity in water flow	Unpredictable Low efficiency May not be useful for some WSN and IoT systems	Metering Aquaculture	[96] [97]
6.	RF	Electromagn-etic waves (RF) are converted into electrical energy	Rectifying antenna/ rectenna	Wi-Fi router: 0.01 μW/cm^2 (2.4 GHz), AM Radio: At 5 Km, 0.02 μW/cm^2 Cell phone: 0.1 μW/cm^2 (900/1800 MHz)	Fully controllable (Dedicated RF energy), Available at all times, Densely available in urban areas	Partially controllable (Ambient RF energy sources) Less available in rural areas, Decrease in efficiency over a long distance (range), resulting in low efficiency	Smart home Aircraft systems Medical Aerospace	[111] [112] [113] [114]

2.3.2 Classification based on intended energy solutions

In this subsection, we present a brief overview of energy transfer (or energy harvesting) solutions in wireless sensor network that are based on intended sources. An energy transfer technique is an alternative method to harvesting energy at the sensor node. Energy transfer in wireless sensor network can also be referred to as a wireless energy recharging technique. This technique is employed to wirelessly transfer energy from a dedicated energy source to an energy harvester or energy receiver at the sensor node. Energy transfer in wireless sensor network can be done in two ways [90], namely wired recharging and wireless recharging. Wired recharging is a direct contact approach that involves the use of wires for interconnection of devices for the purpose of energy transfer. This technique would forfeit the essence of wireless network. Wireless recharging is the process of transferring energy to the sensor nodes in a wireless sensor network wirelessly. This approach is appropriate for energy transfer in wireless sensor network. Examples of energy harvesting systems in wireless sensor networks that have employed energy recharging through wireless energy transfer techniques can be found in references [115], [116], [117]. In [115], a power beacon was employed to transfer energy to the WQ node in a cognitive radio sensor network. The power beacon harvested RF energy from ambient RF energy sources, and delivered the energy harvested through an in-band wireless energy transfer technique. In [116], a cognitive WQ node employed a wireless energy transfer technique to receive RF energy from a set of randomly deployed RF energy sources, here referred to as power beacons. In [117], the authors employed an in-band energy transfer technique to transfer the RF energy harvested by a power beacon (energy source) to the cognitive WQ node in a cognitive radio sensor network.

To support the operation of wireless sensor network applications with various QoS constraints, several energy transfer techniques have been developed. Examples of such techniques include RF energy transfer, energy transfer through laser beam, and coupling-based energy transfer [90], [99], [118]. In what follows, a brief review of the aforementioned techniques is offered.

2.3.2.1 Energy transfer through laser beam

This approach falls in the category of directed radiation and transfers energy in the form of light through a laser beam, usually by exploiting lasers based on solid-state technology. Laser energy is transferred to an energy harvesting sensor node through a high intensity laser beam as shown in Figure 2.11. The transferred laser energy is received by a set of photovoltaic (PV) or solar cells embedded in a panel. Thereafter, the received laser energy is converted into an electrical energy by the PV cell. In the electromagnetic spectrum, laser light covers frequency bands of 30 THz to as high as 3 PHz [90]. So, any frequency bands within the aforementioned range of the electromagnetic spectrum can be employed for transmitting laser energy from the laser energy source to the PV cells of the energy harvester. An example of energy transfer through laser beam can be found in [119] where laser was used to transfer light to the working field of a wireless sensor network application. The laser beam energy transfer technique can be employed to transfer energy over a long distance. Also note that the charging efficiency of this method depends on the distance between the transmitting station and the receiving node. As a result, this method may achieve up to 98% charging efficiency over a distance of 50m [90]. The reason for the high charging efficiency of this method can be attributed to the narrow beam and high intensity of a laser beam, unlike other sources of lights such as infrared, fluorescent, torch, and solar. However, the amount of harvestable energy by the harvesting node is a function of the conversion efficiency of the PV cell type that is embedded in the harvesting node. Also, laser energy transfer through a laser beam is limited by line of sight (LOS). Furthermore, laser energy transfer through a laser beam is potentially harmful to humans. Some of the light in the frequency region of Terahertz and Petahertz can penetrate living organisms and cause severely negative impact.

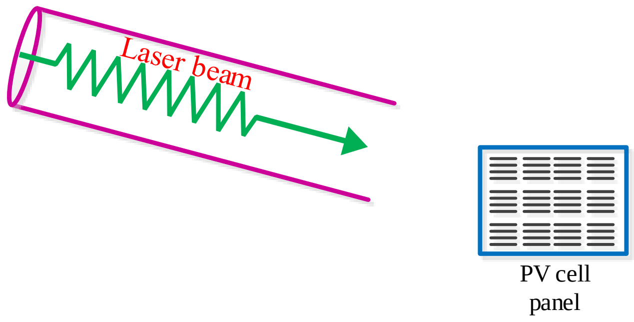

Figure 2.11. Laser energy transfer scenario.

2.3.2.2 RF energy transfer (or electromagnetic radiation)

RF energy transfer can simply be described as the transmission of RF energy through RF wave radiations from an RF transmitter [65], [120], [121]. Consequently, RF wave radiations serve as a vehicle (or medium) for the delivery of energy. It is important to emphasize that RF energy radiation can be achieved in two ways, namely directive and non-directive. In the case of directive radiation, directed antennas, which may include beamforming techniques, are employed. Non-directive radiation may be implemented by employing omnidirectional antennas.

Since electromagnetic radiation covers a frequency bands of 3 kHz to 300 GHz [90], [99] in the electromagnetic spectrum, RF energy can be harvested or transferred in the specified frequency bands through a far-field wireless transmission method [99]. For example, for wireless sensor network applications the radio spectrum of unlicensed ISM such as 902 to 928 MHz (915 MHz center frequency) and 2400 to 2500 MHz (2450 MHz center frequency) can be used to realize the broadcasting of RF energy. RF energy transfer employs a dedicated RF energy source to transfer RF energy to an energy receiver in an energy harvesting sensor node. Dedicated RF energy sources are powerful devices with power transmission capability. In practice, they could be powered either through batteries with higher power or alternating current (AC) input sources. Examples of commercialized dedicated RF energy sources include the Powercaster transmitter, isotropic RF transmitter, and the Cota transmitter [115], [99], [122]. In a similar vein, examples of commercialized RF energy harvesters are the Powercaster receiver [100] and the Cota receiver [99]. As an example, according to [123], [124], [125], it is possible to harvest power that is up to 1.5 mW at a distance of 0.5 m from an RF energy source. Similarly, a 1 μW and a 3.5 mW power have been reported to be harvested at distances of 11 m and 0.6 m respectively based on the Powercaster energy solution at a frequency of 915 MHz [126]. Taking the efficiency of this method into account, an energy charging efficiency of about 75% may be achieved over a short distance in meters, but a decline in efficiency may be experienced over larger distances due to signal attenuation. Note that the efficiency of this method may be enhanced through the exploitation of highly efficient rectennas and energy beamforming strategies [100]. To harvest RF energy from a dedicated RF energy source, an RF energy harvester sends a low-power omnidirectional signal to an RF energy source. Then, the RF energy source transfers the energy requested to the RF energy harvester. Examples of studies where RF energy transfer have been applied are references [27], [28], [115], [116], [117]. For example, this technique has been employed in references [27], [28] to power a wireless sensor network system for monitoring of WQ at water sites.

In RF energy transfer, there is no need for any line of sight between the RF source antenna and the RF energy harvester antenna [90], [99]. Energy transfer is done in an omnidirectional manner by the omnidirectional antennas. Consequently, concurrent energy transfer to several WQ node in the network is possible [99]. However, there is a decrease in the transmitted energy efficiency as the distance between the RF energy source and the RF energy harvester increases. Furthermore, the RF energy received by each sensor node differs a little due to the distance of each RF energy harvester to the RF energy source. This situation is due to the doubly near-far problem [120].

There are several circuit structures for RF energy harvesting and information transmission. They can be classified into four basic categories [99], namely the time switching structure, the power splitting structure, the separated receiver structure, and the integrated receiver structure. Typically, the type of structure employed by a harvesting node determines the operation of such a node in the context of RF energy harvesting and information communication. However, it is important to emphasize that there is a trade-off in efficiency between RF energy harvesting and information transfer, as each of the processes use different circuits with different sensitivities in terms of signal power [127]. In practice, the circuit structures are employed in a line of research known as wireless powered sensor network (WPSN), where the sensor nodes in such network are powered wirelessly by the harvested RF energy. The building of a WPSN system involves two fundamental blocks. Such blocks may involve a separated architecture or a co-located architecture. Briefly, in a separated architecture, an energy source (or transmitter) and a BS (or data gathering node) are differently located, while an energy source and a BS are combined in a co-located architecture. Due to the integration of an energy source and a BS in the case of a co-located architecture, the two components are mostly called a hybrid access point (or HAP), for the sake of convenience [128].

To demonstrate the transfer of RF energy and RF energy harvesting using any of the aforementioned circuit structures, a single dedicated RF energy source, a set of WQ nodes, and a BS are presented in Figure 2.12, while a single HAP and a set of WQ nodes are considered in Figure 2.13. In both cases, the flow of energy and information are represented with a broken line and an unbroken line, respectively. In Figure 2.12, a separated architecture is employed to differently deploy a dedicated RF energy source and a BS, such that the deployed dedicated power source operates as a separate entity to wirelessly transfer RF energy to the WQ node in a sensing field in the DL. The WQ nodes used their harvested energy to transfer the measured information to the BS in a single-hop manner in the UL, in this case. In Figure 2.13, a co-located architecture is adopted to combine a dedicated RF energy source and a BS into a single element, defined as HAP. The HAP performs a dual function, as it transfers RF energy to the sensor nodes in the network in the DL, as well as gathering information from the sensor nodes in the UL. An optional antenna switching system is incorporated in the structures of both Figures 2.12 and 2.13. The consideration of an antenna switching system depends on the used structure (such as time switching structure and power splitting structure). For example, in both time switching structure and power splitting structure, a single antenna may be used, while an antenna switching system is incorporated to control the switching between the energy harvesting system and the data communication system. In a separated receiver structure, each of the energy harvesting and data communication systems has a separate antenna [120].

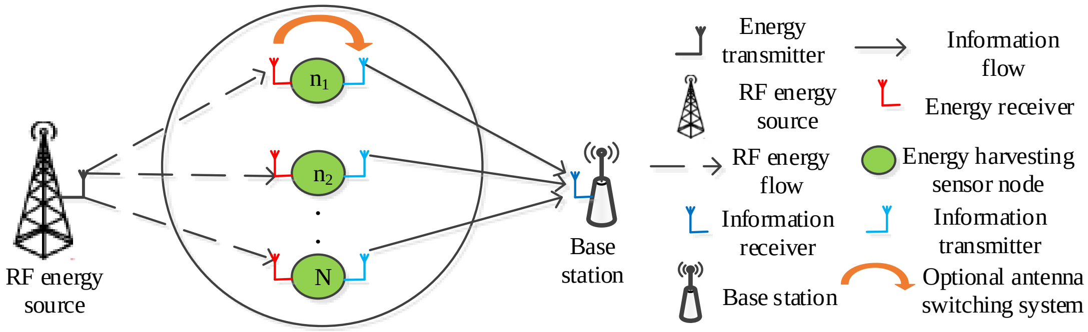

Figure 2.12. RF energy transfer and information transmission based on a separated architecture.

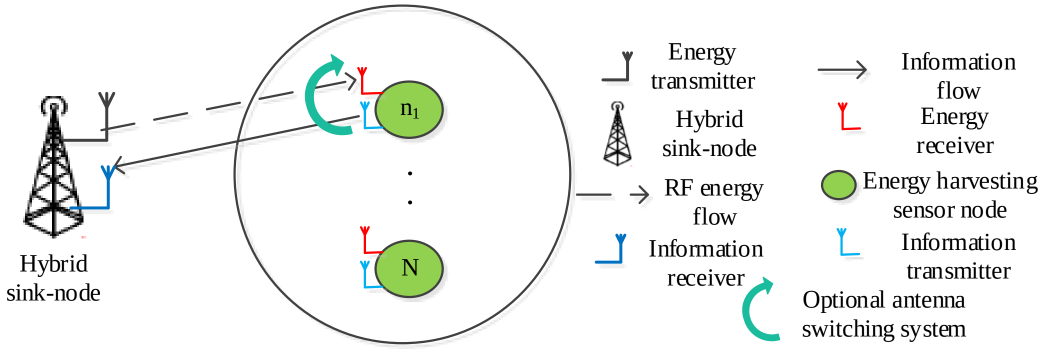

Figure 2.13. RF energy transfer and information transmission based on a co-located architecture

2.3.2.3 Energy transfer through coupling techniques

Coupling techniques are non-radiation based solutions used for transferring energy from a device to another device by exploiting the magnetic fields that exist between the coils of two devices. This technique has been widely explored in wireless and mobile devices to transfer energy and data. Energy transfer using the coupling method can be classified into two major perspectives, namely inductive coupling and magnetic-resonance coupling, and are discussed in the following subsections.

- Energy transfer through inductive coupling: Inductive coupling can be described as a means by which electrical energy is produced and exchanged based on the principle of electromagnetic induction [129]. This technique is employed often in coil based wireless mobile devices and is easy to implement. Inductive coupling obeys the principles of a conventional transformer, whereby the primary side and the secondary side of the transformer are separated and inductively coupled together to transfer energy [129]. The transmission of energy using inductive coupling is achieved when the primary side of a transmitter coil is used to induce a voltage across a receiver's secondary coil placed in the magnetic field region of the transmitter coil. The magnetic fields between the transmitter coil and the receiver coil is used to transfer energy [90]. A descriptive diagram of wireless energy transfer using inductive coupling is given in Figure 2.14.

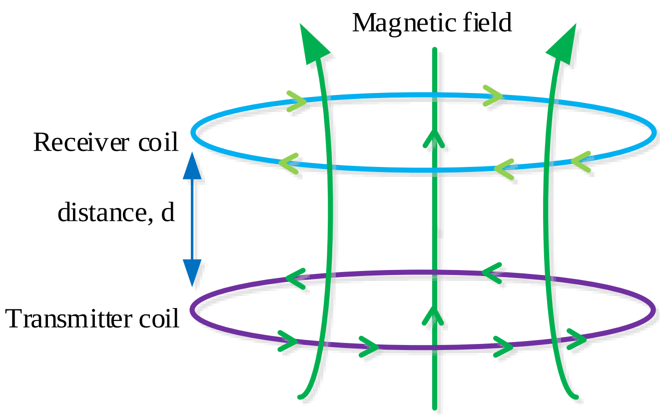

Figure 2.14. Transmission of energy in inductive coupling

The inductive energy transfer technique is characterized by non-radiative behavior [129]. Energy transmission based on inductive coupling is limited by a near-field wireless transmission property, and energy transfer is achieved within few millimeters and few centimeters (typically less than one meter) [99], [130]. In inductive coupling, the efficiency of the energy transferred is determined by the distance between the coils. Thus, this method requires a close coil spacing and alignment for efficient energy transfer. Also, it is important to mention that the two coils must maintain the same orientation for this technique to be operational [131], [132]. As a result, for effective energy transfer from the transmitting coil to the receiving coil, a typical short distance of about 3 cm is required for efficiency. Taking such distance into account, it is possible to achieve an efficiency of about 70% [90]. Unfortunately, as the mentioned distance is exceeded, the charging efficiency begins to depreciate. These drawbacks make this technique unsuitable for energy transfer to remote WQ node, thereby, limiting its application areas to mobile devices such as medical electronic devices and in smart home applications. In addition, it is not a suitable candidate for powering WQ node because of the strict requirements.

- Energy transfer through magnetic-resonance coupling: Magnetic resonance coupling is an interesting means by which energy is wirelessly transferred between two systems, and is characterized by a near-field non-radiative pattern or behaviour [133]. Depending on the transmission medium type [129], electric-based or magnetic-based energy transfer may be employed. In the case of electric-based energy transfer, wireless energy transfer is achieved through electric fields, while wireless energy transfer is achieved through magnetic fields in the case of magnetic-based energy transfer. The energy transmission propagation mode of this technique in either case is omnidirectional [129], [131], and in transferring energy between resonant coils, line of sight is not required [133], [134].

  With the magnetic resonance technique, wireless energy transfer is achieved when electromagnetic coupling is prominent at a shared resonant frequency [90]. For example, in references [135] and [136], when two conductors such as coils couple energy when they are tuned to a resonant frequency of 6.5 MHz and 9.9 MHz, respectively. One of the conductors can be regarded as a transmitting coil, while the other can be regarded as a receiving coil. Different from the inductive coupling technique that requires placing the coils within a close range, with resonance energy transfer can be effectively achieved at a longer distance - within a few centimeters and a few meters. A descriptive diagram of wireless energy transfer using magnetic resonance coupling is given in Figure 2.15.

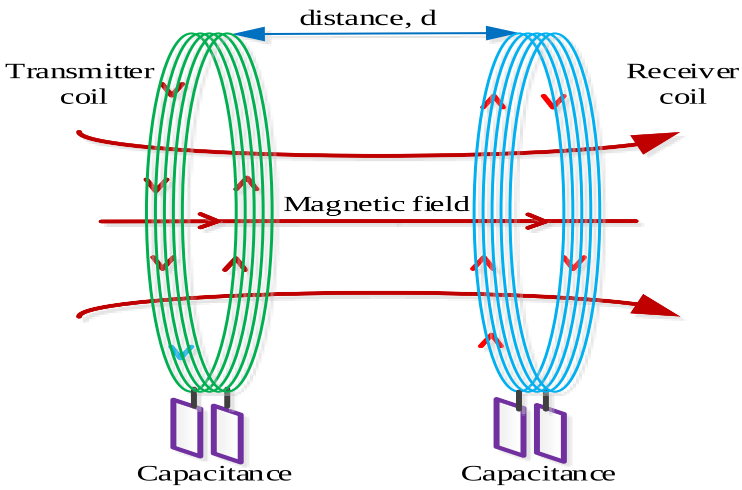

Figure 2.15. Example of energy transfer in magnetic resonance coupling.

The concept of magnetic resonance technique was employed in [134] to transfer energy to the WQ node in a wireless sensor network. The authors developed a wireless charging vehicle that travels periodically in the wireless sensor network working environment and wirelessly deliver energy to the WQ node. In [136], the authors investigated the transfer of energy from a source coil to a receiver coil wirelessly through a non-radiative electromagnetic field. Moreover, examples of commercial solutions based on magnetic coupling techniques can be found in [137-139].

Regardless of its improved wireless transmission property compared to inductive coupling, an effective wireless transmission can only be achieved for relatively small distances, and a charging efficiency of about 60% may be realized at a charging distance around 2 m [135]. Furthermore, a magnetic-resonance coupling based system is complex to implement. All these limitations make this technique unsuitable for transferring energy to remote WQ node, thereby typically limiting its application to mobile devices such as medical equipment.

In summary, the WQ node in wireless sensor network applications are energy-hungry devices, which is exacerbated on a system level by the limited energy budget of the batteries which are traditionally employed to power them. As a consequence, the wide-spread deployment of wireless sensor networks has been limited in practice. To address this problem, energy harvesting from ambient sources has been proposed as an alternative solution to powering the WQ node in a network. Unfortunately, this technique is associated with several constraints, which may not contribute to the advancement of wireless sensor network application in the context of wide acceptability. Such constraints include the intermittent and unpredictable characteristics of energy harvesting solutions that are based on ambient sources, for example in the cases of wind and solar energy sources. With these characteristics, it may be difficult to guarantee the reliability and sustainability of networks that are based on this technique. Due to the limitations of energy harvesting solutions that are based on ambient sources, energy solutions that are based on intended sources have been proposed as a promising solution to ending the energy problems in wireless sensor network systems. The new technique is based on energy transfer and has attracted much attention in recent years. Some of the key advantages of the energy harvesting technique based on the intended sources over the energy harvesting technique based on the ambient sources include deterministic and controllable energy supply [101]. Among the energy solutions that are based on the intended sources are methods such as magnetic-resonance and inductive coupling which are characterized by a near-field property, which limits their transmission coverage and application. Also, they are associated with problems that include energy transmitter's coils alignment and energy receiver's cols alignment [140]. Because of these problems, they cannot be employed for remote energy transmission. Furthermore, energy transmission in an intended laser beam can be obstructed, and it is not considered safe for humans due to its operating regions. RF energy transfer technology is more suitable and promising to advance the successful deployment of wireless sensor networks. One of the reasons for this can be attributed to its far-field characteristic, which makes it possible to conveniently power a sizeable number of WQ nodes in a network using this technique. A summary of the considered techniques is given in Table 2.2.

Table 2.2. Summary of energy transfer techniques.

	Energy transfer techniques	Approach	Mode and field region	Propagation characteristics	Strengths	Weaknesses	Applications/ Solutions	Refs.
1.	Laser beam energy transfer	Transfers energy in the form of light through either a laser beam or a photocell	Radiative mode: Far-field / long distance range	Directional	It covers a long distance, High efficiency, for example 50 m	It is prone to scattering due to atmospheric conditions that include rain, fog, and cloud, Not safe for humans due to its operation regions, it requires line-of-sight	Wireless sensor networks, Satellite solar power, Unmanned aerial vehicles, Elevation climbers in space	[119]
2.	RF energy transfer	Transfers energy through radio frequency waves using antennas such as antenna array	Radiative mode: Far-field / long distance range	Omnidirectional	No line-of-sight, covers a long distance, High efficiency, for example 1.5 m	The energy decreased over a long distance, health and safety challenges	Cognitive radio sensor networks, IoT, Wireless sensor networks, aircraft charging.	[116] [117]
3.	Inductive coupling	Transfers energy through magnetic fields using wire coils	Non-radiative mode: Near-field / short distance range	Semi-directional/it requires alignment	Ease of operation, High efficiency, for example 3cm	It requires close coil spacing and alignment, Short transmission range	Smart home, Medical implants, Industrial applications	[141] [142]
4.	Magnetic-resonance coupling	Transfers energy through magnetic fields using either resonators or tuned wire coils	Non-radiative mode: Near-field / long distance range	Omnidirectional	It does not require line-of-sight, Short transmission range, Safe, High efficiency, for example 2 m	It is complex to implement	Biomedical implants, Industrial applications, Medical equipment, Implantable devices, Smart cards	[138] [143] [144]

2.4 EQUIPPING WQ NODE WITH ALTERNATIVE ENERGY SOLUTION MODELS

Energy is a scarce resource in wireless sensor networks. Energy harvesting technology has recently emerged as a promising approach to the energy-scarcity problem in wireless sensor networks [64-68]. Energy harvesting is a process that involves scavenging energy from either ambient energy or intended energy sources, or from both, in a sensor node's environment through energy harvesting systems and schemes [145]. The harvested energy is converted into electrical energy and is thereafter stored in an energy buffer (or energy storage device) such as super-capacitors or batteries, based on a pre-defined random operation and the used components, such as transceivers or microprocessor with respect to a specified mode of operation [146]. The stored energy is used by a sensor node to power its components. To optimally utilize the harvested energy, energy optimization is necessary. Energy optimization is aimed at maximizing the energy efficiency of a sensor node. It is therefore important to study energy harvesting and energy optimization jointly. Energy optimization is essential because the basic operations of a wireless sensor network, such as data sensing, processing, and communication, are energy-intensive. Energy harvesting wireless WQ node are better replacements to the traditional battery driven wireless WQ node such that the stored energy in an energy harvesting sensor node rechargeable battery is repeatedly replenished through energy harvesting, while the limited energy available in a non-rechargeable battery-powered wireless sensor node depletes with time [147].

Unlike a traditional sensor node without energy harvesting capability, a modern sensor node is empowered with energy harvesting capability. To achieve this, the hardware of a conventional sensor node is equipped with energy harvesting technology. As a consequence, the power unit of an energy harvesting based sensor node is extended by incorporating an energy harvesting system to the power unit [48]. A crucial circuit in an RF energy harvesting system is a rectifying antenna [148]. The rectifying antenna helps to convert RF energy into DC power. Technically, the efficiency of an energy harvesting system is determined by the sensitivity of the signal power transducer. For example, the sensitivity of an energy harvesting system is typically around -30 dBm [149]. As a result of the advances in energy harvesting approaches in wireless networks, an energy harvesting unit, which is also referred to as a recharging unit, can be integrated to an energy management system in the power unit, as shown in Figure 2.16 [145].

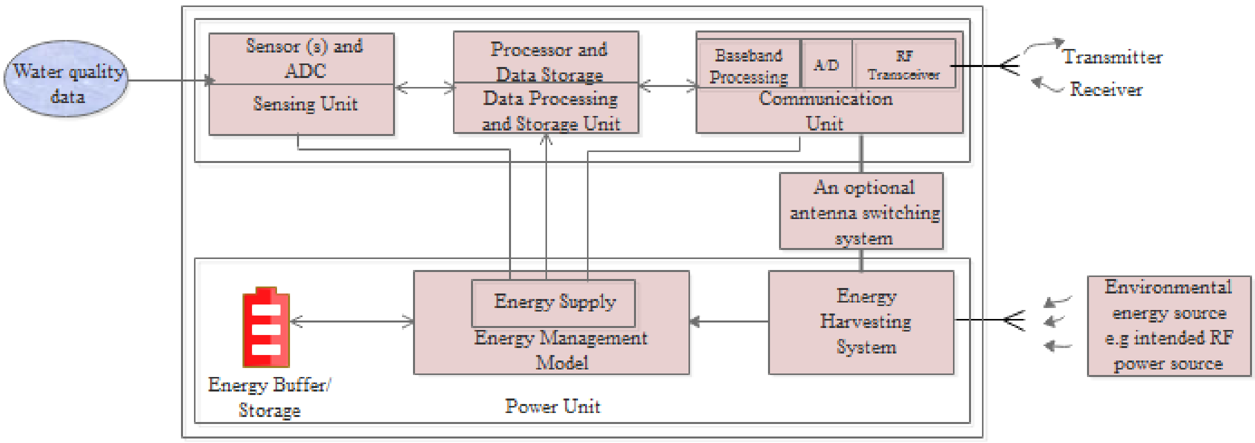

Figure 2.16. Structure of a sensor node equipped with energy harvesting technology.

2.5 COMMON OPTIMIZATION TOOLS EMPLOYED FOR SOLVING ENERGY MINIMIZATION PROBLEMS IN WIRELESS SENSOR NETWORKS

This subsection presents an overview of optimization in wireless sensor networks. Presently, the problem of high energy consumption in wireless sensor networks is one of the major focus areas of the wireless sensor network research community, since this line of research permeates all aspects of a sensor network. Considering the energy problems in wireless sensor networks, and taking into account the unique requirements of wireless sensor networks for WQM applications that include timely delivery of WQ information, reliable QoS (such as throughput rate), sustainable network communications, and the peculiar features of WQM networks in comparison to other types of wireless sensor networks in terms of sampling frequency rate of WQ measurements, processing of the measured data, and communication of measurements in relation to energy cost, it may be difficult to satisfy the requirements of wireless sensor network for WQM applications. Also, it is important to take into account the energy requirements of different WQ nodes in WQM sensor networks for optimizing the total energy consumption of a network as a result of the disparity in energy dissipation among WQ nodes due to their intended measuring tasks. To address the problem of high energy consumption through optimal utilization of energy resources, energy optimization techniques are crucial. For example, in wireless sensor networks, the component that dissipates the most energy in WQ nodes is the RF transceiver. The RF transceiver of the sensor nodes in a wireless sensor network can be controlled by optimizing the rate of power transmission. Importantly, optimization techniques are powerful resource allocation tools that can be applied to wireless sensor networks to address the problem of energy scarcity among the WQ node in a network by minimizing the energy consumption of a WQ node in an efficient manner. This implies that optimization techniques can be employed to control the allocation of power in an optimal manner to solve energy problems such as excessive energy consumption [150]. To address energy consumption problems in wireless sensor networks, the physical (PHY) layer and the medium access control (MAC) of the wireless sensor network protocol stack model can be optimized [151], [152]. As an example, in a sensor node, the choice of decisions at the PHY layer will influence the whole of the sensor node energy consumption and other protocols.

The impact of the PHY layer in wireless sensor network, and on the energy consumption of sensor nodes cannot be overemphasized. Briefly, the PHY layer detects signals (or data streams) and carries out data stream conversion (or data encryption) into suitable signals for transmission over the wireless communication channel. It defines the type of transceiver employed, selection of frequency band, generation of centre frequency, communication medium (such as air), and also includes definition of parameters such as transmission power, modulation scheme, data transmission rate, and data transmission distance (or hop distance). These parameters can be optimized by a network designer to reduce energy consumption.

The MAC layer is responsible for data stream multiplexing, that is, combining multiple signals into one signal. It is also responsible for the detection of the data frame. The MAC layer defines the control of the communication channel (or medium), including error control. These processes are controlled by protocols, which dissipate much of the battery power in wireless sensor networks in the absence of robust energy-efficient optimization strategies.

Energy optimization problems in wireless sensor networks can be classified into two basic perspectives, namely the linear optimization problem and the non-linear optimization problem [150], and they are determined by three basic parameters which are; the objective function, the constraints, and the decision variables. In optimization, the objective function could be a minimization or maximization function, which is a single expression. An important characteristic of a minimization problem is convexity, while the characteristic of a maximization problem is concavity. The constraints may contain several equalities and inequalities, while there could be one or more decision variable(s).

For a better understanding of the structure of optimization problems, a quick review of the general formulation is provided to illustrate the formulation of energy minimization problem in wireless sensor networks. Suppose we have an energy function $f(c,d)$, and we are interested in determining the value for the decision variables c and d that minimizes the energy function $f(c,d)$, where the requirements to be satisfied by c and d are defined by constraints $0 \leq p_u(c,d) \leq P_u$, $\forall\, u = 1, 2, .., v$, $c_a \geq 0, \forall\, a = 1, 2, .., A$, and $d_b \geq 0, \forall\, b = 1, 2, .., B$. Based on the optimization requirements, the optimization problem can then be formulated as:

$$\min_{c,d} \; f(c,d) \tag{2.1}$$

subject to:

$$0 \leq p_u(c,d) \leq P_u \text{ , } \forall \, u = 1,2,..,v \tag{2.2}$$

$$c_a \geq 0, \forall \, a = 1,2,..,A \tag{2.3}$$

$$d_b \geq 0, \forall \, b = 1,2,..,B \tag{2.4}$$

From the above mathematical model, (2.1) is the objective function, which is a minimization problem. Technically, the objective function in (2.1) is the design problem, which is to be minimized in the context of this optimization problem. Equations (2.2) to (2.4) are the constraints, while the decision variables are c and d. It is important to mention that the decision variable(s) is/are typically used to give an insight into the type of the decision(s) to make in an optimization problem. Equations (2.3) and (2.4) are the non-negative constraints for the decision variables. Equation (2.2) gives a power constraint defined for sensors u, where the maximum allowable transmission power of each sensor u has been bounded (or restricted) by P_u. For simplicity, (2.2) can be written as:

$$p(c,d) = \begin{bmatrix} p_1(c,d) \\ p_2(c,d) \\ p_3(c,d) \\ \vdots \\ p_v(c,d) \end{bmatrix},$$

and $P = [P_1, P_2, P_3, \ldots, P_v]^T$ is a vector for power allocation.

An optimization problem is said to be a linear optimization problem by establishing the linearity of the objective function and all its constraint(s), while an optimization problem becomes a non-linear problem once either the objective function or any of the constraints is not linear. Therefore, the linearity or non-linearity of an optimization problem can only be established based on the objective function and the constraints. A wireless sensor network optimization problem is solved by an optimization method in the class of optimization (linear or non-linear) into which such optimization problem falls. Several optimization methods have been developed to seek solutions to various energy problems in wireless sensor networks. The major ones among them are considered in this chapter. Examples of such include linear programming (or classical optimization), meta-heuristics, heuristics, solution based on problem structure exploration, solution based on soft computing, solutions through dynamic programming, and solutions through geometric programming. The reason why several types of optimization techniques are reviewed in this work is that a single optimization algorithm capable of solving all problems does not exist, so an insight into various optimization techniques is essential to solving various energy problems.

2.5.1 Custom methods

Custom-based methods are optimization tools that adopt the concepts of naturally occurring conditions and logical ideas to seek solutions to several categories of optimization problems. They can be classified into two major categories, namely the meta-heuristic methods, and the heuristic methods.

2.5.1.1 Seeking solutions using heuristic methods

Heuristics are algorithms developed by applying the concept of logical ideas. This method is well known for seeking solutions to specific optimization problems in wireless sensor network, and they are often sought to find solutions to hard problems. A reason why methods such as heuristics are sought when classical optimization methods could not solve a non-linear problem is because classical optimization methods only have the capabilities for local optimal solutions. A heuristic algorithm can be developed along with any of the well-developed methods for solving non-linear non-convex problems, specifically when a solution with reduced complexity in terms of time and space resources is desired. A heuristic is always developed for a specific problem. This means that a solution sought through a heuristic method to a specific energy problem is not transferrable to other problems. A good number of energy problems have been solved through the development of problem-specific solutions. Solutions are often sought through a heuristic method when other methods such as classical optimization methods could not solve an energy minimization problem, or when the solutions obtained have high complexities and failed to deliver an expected result within a reasonable period of time [153]. Examples of where heuristics solutions have been developed are in maximizing wireless sensor network lifetime with respect to energy [150], [154]. Due to the high-complexity issue associated with most classical optimization methods, a heuristic algorithm can be developed to reduce the computational complexity, thus, optimizing the usage of wireless sensor network resources in the context of time, energy and memory. Examples of well-developed heuristic methods and studies where they have been applied are water-filling heuristics [155], [156], greedy algorithm [157], [158], and iterative-based and/or recursive-based heuristics [40], [159].

2.5.1.2 Seeking solutions using meta-heuristic methods

Meta-heuristics are algorithms developed by applying the concept of naturally occurring conditions. This method is often used to solve several optimization problems in wireless sensor networks. Typically, meta-heuristics are sought to overcome the limitation of a heuristic solution, which is problem-specific. Meta-heuristics have two fundamental properties that include randomization and best solutions selection. The randomization property of meta-heuristics enables solutions to reach a global optimal solution, instead of being restricted to a local optimal solution, as in the case of classical optimization methods. While the best solutions selection property enables meta-heuristic solutions to reach optimal solutions.

Examples of well-developed meta-heuristic methods are evolutionary algorithms. An evolutionary algorithm is a type of algorithm that simulates the evolution of individual structures by selecting, recombining and reproducing mutations, and thus produces better solutions [153]. Some examples of evolutionary algorithms and where they have been employed are krill herd algorithm (KHA) [160], particle swarm optimization (PSO) algorithm [161], [162], ant colony optimization (ACO) [163], [164], and genetic algorithm (GA) [154], [163], [164], to solve energy problems in wireless sensor network.

Wireless sensor network non-linear optimization problems can be classified into two basic types, namely non-linear convex problem and non-linear non-convex problem. A non-linear convex problem is treated as an LP problem if its convexity can be established. Such a problem can be solved by employing the Lagrangian duality method with Karush-Kuhn-Tucker (KKT) conditions, while the solution to such problem is optimal [165]. However, when the convexity of a non-linear problem is not established, then the problem is regarded as a non-linear non-convex problem, which can be solved through other well-developed methods that include particle swarm optimization (PSO) algorithms [108], genetic algorithm (GA) [166], artificial bee colony, and other newly developed algorithms. Solutions obtained to non-linear non-convex problems are regarded as sub-optimal, near-optimal or close-to-optimal. Meta-heuristics are algorithms developed alongside many well-developed methods to solve a wide-range of optimization problems. Meta-heuristic solutions often work well for the problem studied, thereby limiting the chances of transferring the solution to a particular problem to another problem. This technique is often employed to seek solutions to energy problems that are computationally demanding. Furthermore, meta-heuristic algorithms are developed when there is need for globally optimal solutions.

In summary, meta-heuristics and heuristics are custom optimization tools developed when there is a need for a solution to a problem within a reasonable time frame. Meta-heuristics are developed to seek solutions to a range of optimization problems, while a heuristic solution is problem-specific. However, a meta-heuristic algorithm or a heuristic algorithm developed for a range of problems cannot be transferred to other problems. This is the main drawback of these techniques.

2.5.2 Seeking solutions using linear programming methods

Wireless sensor network energy optimization problems that fall into the class of linear programming (LP), or convex programming, are solved using classical methods. As an example, if functions $f(c,d)$ and $p_u(c,d)$ that represent the energy (or objective) function and the constraints in (2.1) and (2.2), respectively, could be shown to be a convex problem, then it can be solved using the classical methods. To establish that an optimization problem falls into the class of convex programming, two techniques are available, while any one of them can be employed. These techniques are Lagrangian and partial derivatives (either or both first and second). A developed optimization method for providing a solution to an optimization problem is referred to as an optimization problem solver [150]. There are two basic optimization methods for solving wireless sensor network LP problems, namely interior point algorithms and simplex methods. These methods are classical methods that employ well-developed tools used to seek optimal solutions to energy problems developed as an LP problem. Examples of both the interior point and the simplex methods, including studies where they were employed to obtain solutions to energy problems in wireless sensor networks, are the bisection method [165], [167], the Lagrangian duality method [159], [165], [168], the traveling salesman problem [169], [170], the gradient method [159], [171], the dual-decomposition method [168], [172], and the branch-and-bound method [154].

LP methods have a number of advantages, they can provide optimal solutions to optimization problems and they can also act as bounds for the algorithms obtained using other methods [153]. However, solutions provided through classical optimization methods often result in high complexities in terms of computational time and resources [153]. Because of their high complexities, they consume more resources in the context of energy and memory [173]. Solutions with high complexity are not considered optimal in a real-life or practical wireless sensor network scenarios. Moreover, in cases where the solutions provided through classical methods are unreachable or less optimal, non-linear solutions are considered [150], [174]. Thus, a suitable non-linear optimization method can be employed to seek solutions to such problems. More often, because of the structure of energy consumption minimization problems in wireless sensor networks, authors mostly resolve to seek optimization algorithms for non-convex problems.

2.5.3 Seeking solutions through problem structure exploration

Suppose an optimization problem does not fit into a well-researched and well-known category of optimization problem: different techniques are employed such as reformulating the problem, splitting the problem, or finding an approximation of a function. In most cases, the problems of energy minimization in wireless sensor network do not really fall directly into the class of a linear optimization problem. As a result, standard classical optimization methods cannot be directly applied to seek optimal solutions to such problems. In such situations, other methods have been exploited and employed to seek solutions. A very good example of such a method is studying the structure of the formulated energy optimization problem to determine if there are certain parameter(s) that can be modified in a way to turn the problem into a standard problem, and thus, solvable using LP methods. In this manner, the problem becomes easier to solve, and the solution obtained could either be a sub-optimal solution or an optimal solution. The type of solution obtained is determined by the closeness of the reformulated or restructured problem(s) to the initial main formulated problem. A few important approaches based on this technique are examined as follows.

2.5.3.1 Solution based on reformulation method

This method is one of the techniques commonly employed in studies to seek solutions to hard non-polynomial (NP) energy optimization problems in wireless sensor network. Certain features, once identified in a formulated problem, can be exploited to derive a reformulation of the originally formulated problem, without affecting the overall details of the initial problem. The reformulated version of the original problem can then be solved by employing classical optimization methods. A reformulation method has been employed in studies to seek solutions to energy optimization problems. For instance, the authors in [165] and [167] have employed this method to reformulate their original formulated non-convex energy maximization problem into a convex problem in order to seek an optimal solution to their power allocation problem. The major setback of this approach is obtaining the exact structure of some energy problems.

2.5.3.2 Solution based on approximation method

An approximation method is one of the techniques that have been employed in studies to seek solutions to energy optimization problems. In some energy optimization problems, certain parameters in the objective functions or the constraints could render the problem non-linear non-convex, and as a result, such problems do not fit into a standard optimization model, thus making it difficult to solve. One of the efficient ways to solve such a problem is to see if there are approximate substitutes for the parameters that rendered the problem non-linear non-convex. Of course, the substituted approximate function should be close to the original parameter. Furthermore, due to the approximate substitute, the solution obtained to such problem may be regarded as either an optimal solution, or a sub-optimal solution. Solutions obtained through the approximation method are useful because the computational complexity and the time required to arrive at a solution are reduced as a result of the substituted approximate function. Solution by the approximation approach has been employed in various studies to solve energy optimization problems. Examples of studies where an approximation-based method has been applied are found in references [159-177]. For example, in [175], the authors improved their wireless sensor network system energy efficiency by jointly optimizing the transmit power and data bit allocation.

2.5.3.3 Seeking based on linearization method

This method could be applied to a non-linear optimization problem based on the structure of the problem, to seek possible linearization to such a problem. In most cases, energy minimization problems are in non-linear forms. For example, an energy optimization problem automatically becomes a non-linear problem once either the objective function or any of the constraints is not linear. In such a situation, linearization is a useful technique that can be exploited to carefully linearize the function(s) that contains non-linear terms. If the linearization process of the non-linear function(s) is successful, then it becomes quite easy to seek solutions to the optimization problem by employing any of the classical optimization methods, even though the solutions obtained to such problem may be sub-optimal due to the linearization of the original function. Consequently, the type of solution that is obtained to such problem is determined by the closeness of the linearized function to the original function. This method has been explored by the authors in [178] and [179] to convert their non-linear energy optimization problems to simpler ones by linearizing the functions that made the optimization problems non-linear.

2.5.3.4 Solution based on decomposition method

This method is concerned with studying the structure of a formulated energy optimization problem and determines if the problem can be split into sub-problems to make it simpler to solve, but without a negative impact on the problem solution. Each of the decomposed sub-problems is solved individually, and thereafter, the solutions obtained to each sub-problem are combined. A decomposition method has been employed in studies to seek solutions to energy optimization problems. For instance, the authors in [168] and [172] have employed decomposition methods to obtain solutions to their formulated energy maximization problems. The major limitation of this method is that it is not applicable to every energy problem, while this method can also cause some integral parts of the original problem to be omitted in the cause of decomposition.

2.5.4 Obtaining solutions through dynamic programming

This technique is an important optimization algorithm that was put forward around 1950 by Richard Bellman to seek solutions to optimization problems [180]. In dynamic programming, an optimization problem is decomposed into stages (or sub-sub-problems) that are similar to the original problem, but small in size. The stages of the sub-problems are dependent on each other (or they overlap), unlike the case of a divide-and-conquer approach, where a problem is decomposed into sub-problems while each sub-problem is independent. The main reason for decomposing the original problem into stages of sub-problem is to make a decision that optimizes the design problem at each stage of sub-problem. The stages of the sub-problems are solved recursively in a sequential manner during an optimization.

Consequently, the solutions obtained to each stage of the sub-problems are combined together using recursive equations to form a solution to the original problem. The solution obtained to the original problem in dynamic programming may be viewed as a consequence of a sequence of decisions, and the solution obtained may be an optimal one. It is important to mention that the term programming in dynamic programming does not translate to mean computer code, but simply a tabular structure designed to store the solutions to optimization simulations for later use. This makes dynamic programming a computationally efficient technique, as it eliminates the need to further re-compute already computed sub-sub-problems when encountered again. Dynamic programming tools have been exploited in references [152], [181], and [182] to seek solutions to energy problems. For instance, the design goals in [181] were defined to ensure fairness in energy consumption within the WQ nodes in a network, as well as the minimization of the overall network energy consumption, by investigating a network configuration problem in wireless sensor network in the context of topology control and sensor placement. The essence of the sensor placement problem was to find optimal positions to minimize energy consumption, and an optimization-based power control model was sought for the management of the network topology. To address the topology control and sensor placement problems in an energy-efficient fashion, a dynamic programming technique is employed and the problems are treated as sub-problems based on the optimization model. In [152], the energy consumption minimization problem in a wireless sensor network is considered. To seek a solution to the formulated energy problem, a dynamic programming technique is employed, while the energy minimization problem is decomposed into sub-problems. Through the application of the dynamic programming optimization algorithm, an optimal solution was obtained to the original problem. In [182], the authors employed a dynamic programming algorithm to optimize the transmission power of the WQ nodes in a wireless powered sensor network during information transmission in the UL. The optimization of the power allocation is a critical design goal in wireless sensor networks in order to minimize the network overall energy consumption.

One of the advantages of this technique is computational efficiency. It stores its results in a tabular form, which is quickly searched whenever it encounters the same problems that have been previously solved, thus, making this technique a time-efficient approach. Some of the limitations of dynamic programming include its restriction to optimization problems with an overlapping sub-problems structure, and the need for more expertise, which makes this method difficult to develop.

2.5.5 Solution based on the soft computing method

Soft computing is a fairly recent method for seeking solutions to energy optimization problems in wireless sensor networks. The soft computing method involves computer-based software, which controls the resource allocation to the WQ nodes in a network. The software developed for resource allocation incorporates advanced learning and optimization programming techniques, to drive the software during optimization. Examples of such learning and optimization programming techniques resort in the artificial intelligence field, including stochastic algorithms (such as evolutionary strategy, simulated annealing, ant colony optimization, particle swarm optimization), machine learning strategies (such as Q-learning), fuzzy systems (such as fuzzy logic), and artificial neural networks (such as Bayesian network). For instance, a fuzzy logic strategy was employed by the author in [183] to minimize energy consumption in a wireless sensor network. In [184], a stochastic algorithm based on particle swarm optimization was sought to address the problem of energy consumption minimization in the developed wireless sensor network application. Examples of works where Q-learning methods have been explored for energy utilization control are references [185-190]. For example, in [185] a Q-learning technique was exploited to optimize the transmit power of the WQ node in a wireless sensor network in an attempt to minimize the overall network energy consumption. However, this method is difficult to develop, and is also complex to apply to real-life situations.

2.5.6 Seeking solutions using geometric programming

This method is an indispensable optimization tool for solving energy resource allocation problems in wireless networks for efficient utilization of energy resources. It was put forward around 1967 by Zener, Duffin, and Peterson [191-193]. Typically, a geometric programming (GP) tool is employed for minimizing energy consumption in wireless sensor networks by optimizing the transmission power of each sensor node in a network [194]. It is also useful for seeking solutions to maximization problems in wireless sensor networks also. This requires finding the inverse of the maximization problem and recasting it as a minimization problem [195]. GP is a special type of non-linear programming problem, where the technique is used to cast a non-linear problem into a convex problem. To achieve this, a non-linear problem is converted into a geometric problem form as described by (2.5) – (2.7), by turning the objective function of the optimization problem into a linear problem, while the constraints are cast as non-linear functions. The general formulation of a geometric optimization problem is developed by representing an objective function in a posynomial form and minimizing it over monomial equality and posynomial inequality constraints, as described in (2.5) – (2.7).

$$min \;\; f(c) \tag{2.5}$$

subject to:

$$f_a(c) \leq 1, \forall\, a = 1, 2, .., q \tag{2.6}$$

$$d_a(c) = 1,\; \forall\, a = 1, 2, .., j \tag{2.7}$$

From the above mathematical derivations, (2.5) and (2.6) are posynomial functions that results from the addition of the monomial functions $f, \ldots, f_q$, $a = 0, 1, 2, .., q$, while c_a are variables and should be positive numbers such that $c_a > 0$. It is important to note that a monomial means a single function. Equation (2.7) represents monomial functions containing d_a, $a = 1, 2, .., j$ and is defined by $d: \Re_+^j \rightarrow \Re$. Examples of well-known computational techniques that can be applied to GP problems are primal methods (such as primal decomposition) and dual techniques (such as dual decomposition and Lagrangian duality). The GP technique has been employed by the works in references [196-198] to seek solutions to energy minimization problems. For example, the authors in [196] and [197] did a double transformation in their work. First they transformed their formulated energy consumption minimization problem, which is a non-convex problem, into a GP problem. Thereafter, the GP problem was transformed in to a convex problem.

In summary, the critical optimization methods that are exploited and employed by researchers in literature to seek solutions to their formulated energy consumption problems have been examined and grouped, discussing their strengths and weaknesses. The synopsis of the optimization solution methods is presented in Table 2.3. Currently, a single optimization algorithm that is capable of solving all problems does not exist. So, choosing an algorithm to seek a solution to an optimization problem is a critical design decision. The reason for this is that the suitability of an optimization algorithm will determine the optimality of the type of solution obtained to a particular problem. Consequently, choosing an efficient algorithm to an optimization problem is essential. Moreover, due to the energy problems in wireless sensor networks, energy resource optimization is a crucial design objective for effective utilization in wireless sensor network applications. In addition, one of key requirements of wireless sensor network systems for WQM application is energy efficient information transmission [57]. To meet this requirement, optimization is an important tool to control the power allocation process in an efficient manner, thus, minimizing energy.

Table 2.3. Optimization solution techniques to energy problems in wireless sensor network.

	Optimization techniques	Solution methods	Strengths	Weaknesses	Ref.
1.	Heuristics	Water-filling algorithm, greedy algorithm, iterative and recursive based algorithms, etc.	It has low computational and time complexity. It provides a quick solution to energy problems	It is problem-specific and it cannot be transferred to other energy problems.	[153]
2.	Meta-heuristics	Particle swarm optimization, genetic	It is employed to solve a	Solutions obtained through this approach	[165]

		algorithm, ant colony optimization, etc.	wide range of energy problems	cannot be transferred to other energy problems	
3.	Linear programming	Interior point methods and simplex methods. Examples of interior point methods are Lagrangian duality, bisection method, traveling salesman problem, etc. Examples of simplex methods are branch-and-bound method, dual-decomposition, etc.	It gives an optimal solution to energy problems. Furthermore, the solutions provided by this approach can act as a lower bound or an upper bound to other solution modes.	Solutions obtained through this approach often have high computational and time complexity. It is not all energy problems that fall into this category of standard optimization models.	[153] [173]
4.	Solutions based on problem structure exploration	Approximation method, reformulation method, decomposition method, etc.	It gives a low computational and time complexity solution. It gives a near-optimal or optimal solution.	The restructured problem may not be the exact structure of the original problem, as the right form of certain parameters in the original problem may be difficult to obtain	[177]
5.	Dynamic programming	Dynamic game algorithm	It has a low computational and time complexity. It gives an optimal solution	It can only be applied to optimization problems with overlapping sub-problems structure. It is different to develop because of the requirement for technical-know-how.	[180] [181]
6.	Soft computing	Fuzzy systems, stochastic algorithm, Q-learning	It is a computer based software that incorporates advanced learning and optimization programming techniques, to solve resource allocation problems.	It is difficult to develop, as well as complex to apply to real-life situations.	[186]
7.	Geometric programming	Primal methods and dual techniques	It gives a low computational and time complexity. It gives a global optimal solution	It can only be employed if a problem is successfully transformed into a GP standard form.	[192] [193]

It is important to mention that two elements are paramount in achieving simple, low-cost, fast response time and energy-efficient wireless sensor network applications. The two key elements include energy supply from a suitable energy source through either energy harvesting techniques or energy transfer methods, and energy consumption minimization through energy optimization techniques. These issues have been discussed as part of the contributions of this work.

In outline, water contamination is an issue that has plagued the public with health issues, both in the developed and in the developing parts of the world. To address this problem, effective WQM is important to achieve good WQ. Due to the shortcomings of existing WQM analytical approaches and the risks environmental contaminants and water pollutants posed to human health, there is a need to develop energy-efficient wireless sensor systems to address the challenges of the existing WQM systems in a timely manner.

2.6 OPEN-ENDED PROBLEMS ON ENERGY-EFFICIENT STRATEGIES FOR WIRELESS SENSOR NETWORKS IN WQM APPLICATIONS

In this thesis, an attempt has been made to examine a wide range of energy-efficient strategies in wireless sensor networks for WQM applications. The techniques involve several energy-efficient solution models based on optimization techniques, energy harvesting techniques, and wireless energy transfer techniques. The observations made, along with suggestions for further directions on improving the examined energy-efficient solution models are discussed in the following sections.

- Observations and further directions on energy harvesting techniques in wireless sensor networks for WQM applications: The energy harvesting concept simply has to do with energy scavenging from various energy sources. This is done with the help of an energy harvesting module in a sensor node. RF energy harvesting seems to be more promising for the realization of low-cost and low-power WQ node, but the partially controllable nature for ambient sources is challenging. As a result, efficient prediction models should be investigated and developed for ambient RF energy harvesting. Furthermore, solar energy harvesting seems to have a high power value and is fully controllable, but it is confronted with a number of setbacks such as the inability to function in dark environments. Also, the size of solar panel determines the amount of harvestable energy, while its components are costly. This contradicts the design of a low-cost and portable WQ node. Therefore, further research should concentrate on small panels that can address appropriate wireless sensor network node form factor. Low-cost solar panels should be investigated further to achieve the aim of low-cost WQ node.

- Observations on research issues on wireless energy transfer in wireless sensor network for WQM applications: Among the reviewed wireless energy transfer techniques, the RF energy technique seems to be a promising solution compared to other techniques. The following observations are made:

  1) Most of the works on wireless energy transfer (WET) solution models assumes single-hop WET, which may not always be an ideal approach for energy provision and saving in wireless sensor network [1], [29].

  2) Wireless WQ nodes are energy-hungry devices due to the complexities in various computational schemes. Consequently, energy consumption is a major concern in wireless sensor network [1].

  3) There is a need to investigate and develop more efficient methods for energy harvesting [1], [199], [200].

  4) Wireless sensor networks are often powered by intended RF sources, but there is large loss of energy during energy from intended RF power sources [1], [199], [200], [99].

     a. In RF energy harvesting or transfer, the harvesting rate of RF energy depends on several factors such as the RF receiver antenna’s direction, its gain, and the rectifying circuit [199], [200].

b. The performance of RF energy harvesters is limited due to a fixed amount of RF energy that can be supplied by practical sources, a low conversion efficiency of the receiver, and low receiver power gain [199], [200].

Based on the above discussions, the following suggestions for further improvements can be made:

- Multi-hop WET: further studies should investigate multi-hop WET to improve energy saving and efficiency of energy transfer [29].

- Efforts should be intensified on developing improved RF energy harvesters, with more support for multiple frequency band harvesting [1], [99], [199], [200].

  1) Beamforming antennas: consideration of antenna arrays for energy beamforming to enhance the energy transfer from an intended RF power source to the WQ nodes in a wireless sensor network, is a key future design strategy [99], [199], [200]. The concept of multiple antenna beamforming may be useful since it has the potential to minimize the amount of energy loss during energy broadcasting compared to a single antenna method. It does not have the capability to only enhance the efficiency of energy, but also information transfer efficiency.

  2) High efficiency rectennas: the enhancement of rectenna efficiency should be considered for improved RF-to-DC power transformation [99], [199], [200].

  3) RF energy receiver circuits: the sensitivity of the RF energy harvester's circuity should be improved to allow conversion of low-power RF waves [99], [199], [200].

- Optimization techniques are vital tools for seeking solutions to various energy problems in wireless sensor networks. Energy minimization problems that fall in the category of standard optimization models are easily solvable by employing classical optimization methods such as linear programming (LP) and convex optimization. It is observed that there is no particular standard for developing solutions to energy problems. Also, the developed solution models for energy problems seem to be disjointed. For similar problems, diverse approaches are used to formulate the objective functions, the decision variables, and the constraints. This makes it difficult to determine the focal point in several energy problem definitions [1], [173].

Several energy models have not considered a number of factors that would have made energy problems more practical. For example, authors have not been paying much attention to the aspect of heterogeneity in wireless sensor networks in their problem development. The consideration of the concept will provide an opportunity for more practical cases in wireless sensor networks [1].

Such issues can be attributed to the following reasons:

1) Optimization as a vital tool employed in seeking solutions to energy problems is a dynamic tool with various interpretations. This makes it difficult to arrive at a generalized solution model to seek solutions to energy problems [1], [173].

2) It is difficult to capture every detail of wireless sensor networks in a single model. Consequently, the development of a single energy model that addresses every important detail is not pragmatic [1], [173].

Based on the above discussions, the following suggestions need further investigation in order to further enhance the productivity of energy models in wireless sensor network for WQM applications:

- Energy consumption models in wireless sensor network: low energy consumption models should be further investigated to increase the network lifetime of WQ node in wireless sensor network applications [1].

- Development of efficient power management strategies: power management strategies with efficient dynamic policies that optimize a sensor node's behaviour based on the energy available, should be further investigated [1], [173]. This is important when attempting to optimally make do with the available energy. To enhance the energy efficiency of a sensor node, efficient power management strategies are crucial. No matter how highly efficient the rectenna of a harvesting node is, without efficient power management strategies in place, such efforts may not guarantee a better performance.

- Heterogeneous networks / WQ nodes: a resemblance of heterogeneity can occur in wireless sensor networks, and future studies should pay more attention to considering the possibilities of heterogeneity by making proper classification of energy problems in wireless sensor networks. By doing so, more practical energy models would be realized [1].

- Development of energy-efficient physical layer schemes: in order to make the dream of wide-spread deployment of wireless sensor network applications a reality sooner, the development of energy-efficient schemes should be further investigated with the view of achieving low-power units [1], [173].

- Development of strategies for optimizing the overall network energy efficiency of wireless sensor network in WQM applications: the development of efficient strategies to optimize the overall network energy utilization of wirelessly powered wireless sensor network in WQM application. A suitable strategy in this direction is wireless powered sensor network (WPSN) system. WPSN is a new field of research that currently seeks energy efficient strategies, which are still open problems. The need for such strategies could be attributed to the varying energy consumption rates of the WQ nodes in a network as a result of factors that include the network topology (such as star and cluster), the transmit power, and sensor distances to the base station. Without putting efficient strategies in place, the overall energy consumption of such system is negatively impacted as more energy is consumed by the system when the aforementioned conditions are experienced in a network [1].

- Development of efficient wireless powered sensor network systems: due to the inherent doubly near-far situation in WPSN applications - a practical issue in network designs that causes unfairness among the sensor nodes in a network in the context of the energy received, as well as the energy spent on data transmission to the base station - efficient resource allocation optimization schemes are required to realize energy efficient WPSN systems. This is currently an open research problem in practice [1].

2.7 CHAPTER SUMMARY

The key objectives of this chapter were to present a detailed and in-depth review of the different energy efficient solutions for the wireless sensor network systems in WQM applications. The survey has been able to identify the critical shortcomings and challenges of wireless sensor network in WQM, the peculiarities of wireless sensor network for WQM and its specific problems which makes more exacerbating, and this consequently makes the investigation of solutions more difficult. To seek solutions to the problems of wireless sensor network for WQM, this chapter has provided various reasoning, methods, and ideas that have been explored and exploited by the researchers in the wireless sensor network for WQM research community in addressing the problems of wireless sensor networks in WQM to seek viable solutions. Based on the review carried out, various open-ended problems which are limiting barriers to wireless sensor network systems in WQM were identified. Consequently, various suitable ideas were postulated for potential investigations. It is worth noting that the ideas presented in this chapter provide essential considerations and directions for the investigations carried out in the subsequent chapters.

CHAPTER 3 OPTIMIZING THE ENERGY AND THROUGHPUT OF A WATER-QUALITY MONITORING SYSTEM

3.1 CHAPTER OVERVIEW

In this chapter, a new approach to the maximization of energy and throughput in a wireless sensor network applied to water-quality monitoring, is presented. The overview of each section in this chapter is provided as follows. In Section 3.2, the background of the constraints of wireless sensor networks as well as the scarceness of energy resources in wireless sensor network systems dedicated to the monitoring of water quality are presented. In Section 3.3, the related works as well as crucial issues are discussed including the major contributions of the chapter. In Section 3.4, a multi-network, multi-sensor, and multi-source (MNMSMS) system based on the concept of wireless information and power transfer (WIPT) for water-quality monitoring use case, is designed. The mathematical models for the system is also presented in this section. In Section 3.5, a new approach to the maximization of energy and throughput in a proposed WIPT system for WQM is designed. Section 3.6 presents the joint optimization of the energy harvested by sensor nodes and their information-transmission rate using a sum-throughput technique, while Section 3.7 presents simulation experiments and discussion. Section 3.8 gives the summary of the chapter.

3.2 BACKGROUND

In Chapters 1 and 2, key fundamentals on wireless sensor networks have been discussed. Based on the explanations in the previous chapters, it is easy to summarize that wireless sensor networks are useful and promising tools for efficiently monitoring the quality of water in a timely manner. Unfortunately, wireless sensor networks are confronted by several resource constraints that range from communication capabilities, limited energy, low processing capabilities, to limited memory for data storage [50], [51], due to the low-cost and small-size requirements of sensor nodes and other technologies used in wireless sensor networks. Among the aforementioned constraints in resources, energy is the most crucial resource of all [52]. The main reason for its high significance is that all the components of a sensor node depends on it, as it is used for powering sensors, micro-controllers, and communication modules. Energy limitation has been a long-standing issue in wireless sensor network applications [29], [53-55], while seeking solutions to the problem has been an active area of research in recent years. Typically, when there is a lack of energy in a network, one can say that there is an energy crisis in such network, which is technically referred to as energy scarcity. This is an indication that energy resource is a scarce commodity among the energy-hungry WQ node in wireless sensor networks. The energy scarcity problem in wireless sensor networks is a major issue that hinders the development and the continuous popularity of wireless sensor network applications [30-32]. The scarceness of energy resources in wireless sensor network systems dedicated to the monitoring of WQ is a germane issue that affects the productivity of wireless sensor networks in WQM applications in terms of network sustainability and throughput. Considering the assuring promises of wireless sensor networks in WQM, it is therefore a worthwhile investment to seek solutions to the issues that currently hinders the productivity of wireless sensor network solutions in WQM applications. Also note that research activities are presently ongoing to make wireless sensor networks achieve their end goals in WQM applications within wireless sensor networks tight constraints.

To address the limitations associated with wireless sensor network systems as discussed, several energy efficient techniques that can be employed have been provided and discussed in Chapter 2, for example, energy harvesting from sustainable sources and energy utilization optimization.

To further improve the productivity of wireless sensor network in WQM, it is profitable to carry out investigations on the use of energy harvesting technique and optimization methods to improve the availability of energy in the network, optimize the utilization of energy, and enhance the system's throughput.

To seek solutions to the mentioned issues above, WIPT and multi-network strategy are investigated in this chapter as promising techniques. Importantly, by introducing multi-network strategy into wireless sensor network, how the limiting barriers and constraints can be efficiently tackled is revealed in this chapter, to achieve a better productivity in the network.

3.3 RELATED LITERATURE

The concept of WIPT has recently gained particular attention in the research community due to continuous growth in the wireless recharging of wireless sensor networks. However, the existing solutions developed for wireless sensor network systems based on the WIPT concept are confronted by energy harvesting unfairness, and unfair allocation of the information-transmission rate among sensor nodes [201]. In an attempt to balance the trade-off between energy harvesting time and information-transmission rate allocation, a few solutions have been developed. For example, in [202], the authors developed a single-network, multi-sensor, single-source WIPT system. The authors considered concurrent energy harvesting and information transmission in the same frequency channel, and employed a cancellation scheme to reduce the effect of self-interference due to both these functions being in the same channel at the same time. In [203], a wireless body area network WIPT system was developed.

The authors proposed two different protocols to optimize the information-transmission rate of each sensor node to the single access point through balancing the energy harvesting time and the information-transmission time of their WIPT system. In [128], the authors developed a single-network, multi-sensor, single-source WIPT system for implementation in a dynamic scenario. To address the problem of unfair information-transmission rate allocation among the sensor nodes, the authors employed a sum-throughput approach to maximize their WIPT system throughput based on fading channel power gain with a single dedicated RF energy source. In [204], the authors developed a WIPT system with a single multi-sensor network, but with multiple sources. The problem of unfair information-transmission rate allocation among sensor nodes is addressed by maximizing the sum-throughput of their WIPT system, based on the fading channel power gains associated with multiple dedicated RF energy source.

The problem of energy harvesting unfairness and unfair information-transmission rate allocation in WIPT systems may be improved beyond the solutions presented in [128], [202-204]. The multi-sensor, multi-source WIPT system proposed in this chapter expands on [204] by deploying multiple dedicated RF energy source to address the energy harvesting unfairness problem between multiple groups of sensor nodes in a static environment, by employing a TDMA protocol and a sequential energy harvesting and transmit protocol. In [204], the sensor nodes deployed near to the dedicated RF energy source harvest more energy compared to the sensor nodes deployed far from the dedicated RF energy source due to the doubly near-far problem [205]. Consequently, there is energy harvesting unfairness between the sensor nodes in the single-network WIPT system. In the proposed WIPT system, the sensor nodes that ought to be far from the dedicated RF energy source are deployed in another class of network than those close to the dedicated RF energy source, based on a maximum distance threshold between the dedicated RF energy source and the sensor nodes.

Different from the reviewed works above, the work in this chapter focus on the development of a multi-network, multi-sensor, and multi-source system for powering a water-quality monitoring system, while the goals of fair energy harvesting, interference mitigation, and fair allocation of information-transmission rates, among the sensor nodes are ensured.

Furthermore, the essence of this chapter is to ensure that the sensor nodes are able to harvest a sufficient amount of energy required to transmit their sensed water-quality data to the data base station with the expected QoS, while the achievable throughput of the system is also increased. The key contributions of this work include:

- The formulation of TDMA model for energy harvesting and information transmission for a multi-network, multi-sensor, and multi-source system.

- Based on the TDMA protocol proposed, we jointly optimize the energy harvesting time and the information-transmission time of each sensor node *n* and *m* in the DL channels and the UL channels respectively, by maximizing the sum-throughput of the multi-network, multi-sensor, and multi-source system using convex optimization methods [206].

- Efficient multi-network, multi-sensor, dedicated RF energy source selection, allocation, and information-transmission algorithms were developed for efficient dedicated RF energy source selection and allocation for fair energy harvesting among sensor nodes *n* and *m*, and fair information-transmission rate allocation.

This chapter is divided into the following sections: Section 3.4 presents the model of the proposed multi-network, multi-sensor, multi-source system in a static environment, and the TDMA model proposed. Section 3.5 presents the mathematical formulations to optimize the TDMA protocol proposed for the system. Section 3.6 presents the energy-harvesting and information-transmission rate joint optimization problem. Also, efficient algorithms for dedicated RF energy source selection, allocation, and information transmission are discussed. Section 3.7 presents the system simulation results based on the achievable sum-throughput and fairness to validate the sum-throughput optimization problem. Section 3.8 concludes this chapter.

3.4 METHODOLOGY

3.4.1 System model

In the system model, we consider an energy harvesting wireless sensor network that consists of a multi-network, multi-sensor, and multi-source WIPT system. Let $\{n_1, n_2, \dots, N\}$ denote the set of water-quality sensor nodes n in Network 1, and $\{m_1, m_2, \dots, M\}$ denote the set of water-quality sensor nodes m in Network 2. The sensor nodes n and m are deployed in a predetermined manner at some strategic positions for effective monitoring and acquisition of vital parameters in a water-monitoring site as shown in Figure 3.1. The body of the water to monitor is channelled into an improvised man-made water-monitoring section in an enclosed environment that provides a suitable platform for the attachment of the water-quality sensors, and a continuous flow of water as in [207]. Let $\{g_1, g_2, \dots, G\}$ denotes the set of dedicated RF energy source operating in a licence-free ISM band. Since the sensor nodes are deployed in a predetermined manner, their distance to the dedicated RF energy source can be easily controlled. To achieve this, a multi-network WIPT system is considered. In the system, only g_1 represents both a dedicated RF energy source and an information receiver or base station. This is capable of both energy transmission and information reception to and from sensor nodes n and m, while other dedicated RF energy source g can transmit energy to the sensor nodes n and m in their allocated time based on the knowledge of channel-state information (CSI). To avoid the problem of destructive interference often experienced in the channels in multi-source systems due to multiple energy transmissions by the dedicated RF energy source, a controller is employed. The controller connects all the dedicated RF energy source to itself and controls when a dedicated RF energy source g will transfer energy to the sensor nodes n and m, thus eliminating the possibility of the occurrence of any destructive interference. Also, the controller turns the dedicated RF energy source g on and off at the calculated time-slots based on the channel conditions using the proposed dedicated RF energy source selection algorithm which is implemented on the controller. Furthermore, the energy received by each sensor node n and m in each energy harvesting time-slot is reported by each sensor node to the controller.

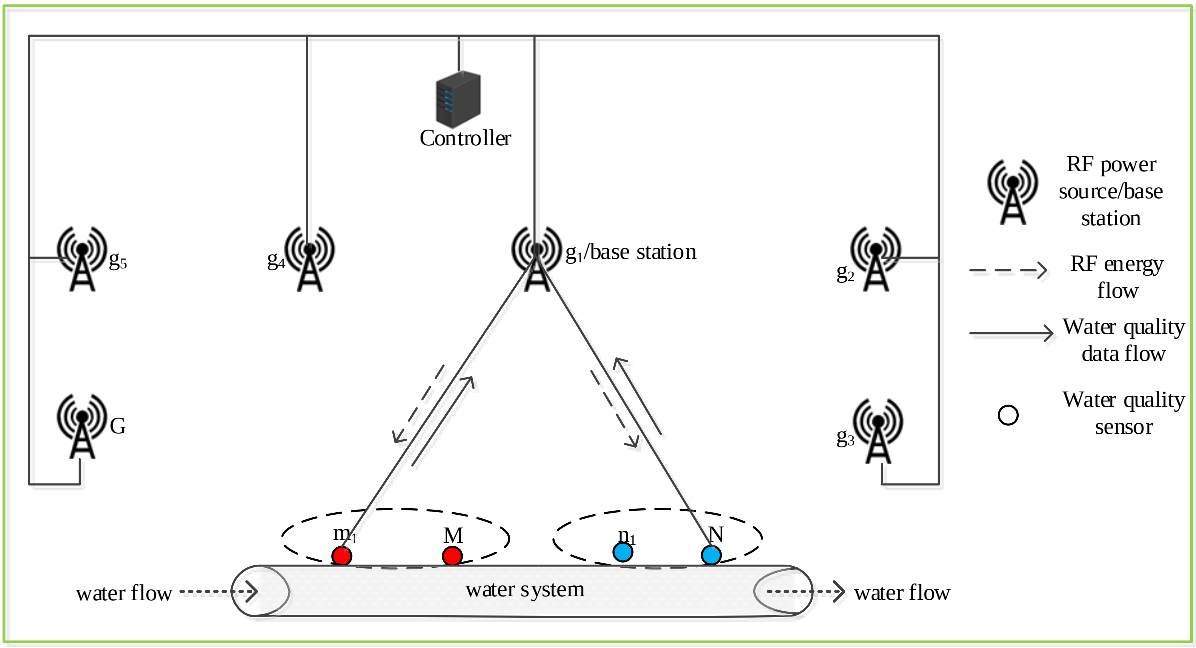

Figure 3.1. System model for a multi-network wireless information and power transfer (WIPT) system.

The sensor nodes *n* and *m* are connected in a single-hop manner, and each of the sensor node sends its independent information about the water-quality parameters of the site that include pH, bacteria, to the base station g_1. The base station g_1 delivers the received information to a water-quality monitoring center through a gateway connected to an Internet service. Each of the sensor nodes *n* and *m* in networks 1 and 2 is equipped with an omnidirectional antenna that operates on the TDMA model in Figure 3.2, such that either the information receiver or the RF energy harvester is connected to the antenna at a given time.

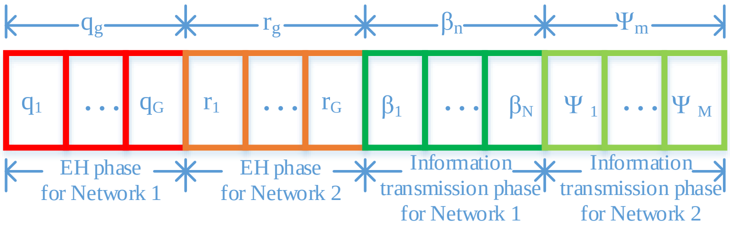

Figure 3.2. Proposed energy harvesting and information-transmission TDMA model.

To prolong the network lifetime of the WIPT system, in each information-transmission time-slot, a fraction of the energy harvested is used for information transmission, while the remaining energy is stored in the energy storage, and it is used for running the basic operations of each sensor node. To avoid interference in energy harvesting and information transmission among the sensor nodes *n* and *m*, and the multiple dedicated RF energy source g, an orthogonal time-slot is allocated to each dedicated RF energy source g to transmit energy to each sensor node *n* and m to transmit its sensed water parameter information to the base station g_1. The sensor nodes *n* and *m* harness energy from the dedicated RF energy source g in the DL channels, while they transfer their independent acquired water parameter information to the base station g_1 in the UL channels. In the TDMA model proposed for the multi-network, multi-sensor, and multi-source WIPT system, since the sensor nodes are deployed close to the dedicated RF energy source, an optimal shorter and equal energy harvesting time is allocated to the sensor nodes. Furthermore, since the sensor nodes are deployed in a predetermined manner, some of the sensor nodes are far from the base station g_1, resulting in a doubly near–far problem. This problem is addressed by allocating an optimal longer information-transmission time to the sensor nodes in order for them to have sufficient time to transmit their independent information.

3.4.2 Propagation channel model

In this chapter, energy and power are used interchangeably. Since the wireless sensor network application environment is assumed to be static, the channel from a dedicated RF energy source g to sensor nodes n and m is modelled as a quasi-static block fading model, and the channel gains are obtained as a feedback from the sensor nodes. The channels from sensor nodes *n* and *m* to the base station g_1 in the UL and the reversed DL channel from a dedicated RF energy source g in the DL are represented with complex variables $\tilde{a}_{g,n}$ and $\tilde{b}_{g,n}$, and $\tilde{f}_{g,m}$ and $\tilde{h}_{g,n}$ for Network 1 and Network 2, respectively, while the channel power gains are $a_{g,n} = |\tilde{a}_{g,n}|^2$ and $b_{g,n} = |\tilde{b}_{g,n}|^2$, and $f_{g,m} = |\tilde{f}_{g,m}|^2$ and $h_{g,m} = |\tilde{h}_{g,m}|^2$ for Network 1 and Network 2, respectively. Also, the CSI is assumed to be known to the dedicated RF energy source g, thus, energy is adaptively transferred based on the channel conditions. The dedicated RF energy source g uses the CSI to access sensor node *n* and *m*, and transmit an optimal energy to each sensor node in an allocated time-slot.

The entire time-slots q_g is dedicated to Network 1 for energy harvesting, while the entire time-slots r_g is dedicated to Network 2 for energy harvesting. Network 1 transmits its information over the time-slots β_n, while Network 2 transmits its information over the time-slots Ψ_m. The operations of the two distinct networks based on the proposed TDMA protocol are described as follows.

Network 1: In each given energy harvesting time-slot q_g, according to the TDMA model presented in Figure 3.2, the first time-slot with a length of $0 \leq q_1 \leq 1$ is assigned to a dedicated RF energy source g to transfer energy to sensor node *n* in the DL, while the time allocated to sensor node *n* to transmit its information in the UL to the base station g_1, over channel $a_{1,n}$, is represented with β_n, *n* = 1, ..., *N*, with a length of $0 \leq \beta_n \leq 1$. Therefore, the time allocated to a dedicated RF energy source g to transmit energy to sensor node *n* in Network 1 in the DL and the allocated time to sensor nodes *n* to transmit their independent information in the UL is defined by Equation (3.1) as:

$$\sum_{g=1}^{G} q_g + \sum_{n=1}^{N} \beta_n \leq 1 \tag{3.1}$$

The received power at sensor node *n* from a dedicated RF energy source is given by (3.2) as:

$$x_{g,n} = \sqrt{b_{g,n}}x_{A,g} + z_n, n = 1, \dots, N \tag{3.2}$$

where $x_{g,n}$ and z_n represents the received signal and the background noise at sensor node *n* from a dedicated RF energy source g respectively. $x_{A,g}$ denotes an arbitrary complex random signal dedicated RF energy source g transmit which satisfies $E\left[\left|x_{A,g}\right|^2\right] = P_{A,g}$, where $P_{A,g}$ represents the transmit power of a dedicated RF energy source g. The notation $E|.|$ denotes an expectation operator, while $|.|$ represents the magnitude of an argument. The transmit power $P_{A,g}$ is assumed to be large enough, thus, the background noise at the receiver *n* is negligible. Therefore, the amount of energy sensor node *n* harvest in the DL in each time-slot from a dedicated RF energy source g is expressed by (3.3) as:

$$E_{g,n} = \eta_n P_{A,g} b_{g,n} q_g, g = 1, \dots, G, n = 1, \dots, N \tag{3.3}$$

Furthermore, the total energy sensor node *n* harvest from the dedicated RF energy source g is given by (3.4) as:

$$E_n = \eta_n \sum_{g=1}^{G} P_{A,g} b_{g,n} q_g, n = 1, \dots, N \tag{3.4}$$

where η_n is the energy-harvesting efficiency of sensor node *n*, $0 \leq \eta_n \leq 1$, *n* = 1, 2, ..., *N*. It is assumed for convenience that $\eta_1 = \cdots = \eta_N = \eta$. After harvesting energy in the DL phase, a fixed fraction of the energy harvested based on (3.4) is used by each sensor node *n* to transmit its independent information in the UL to the base station g_1. The average transmit power of sensor node *n* for information transmission, is denoted by P_n and is calculated using (3.5):

$$P_n = \frac{\varsigma_n E_n}{\beta_n}, n = 1, \dots, N \tag{3.5}$$

where ς_n denotes a fixed fraction of the energy harvested used by sensor node *n* to transmit its independent information in the UL to the base station. For the purpose of simplicity, it is assumed that, $\varsigma_n = \cdots = \varsigma_N = \varsigma$, while the remaining portion of $1 - \varsigma$ is used for operating the sensor node *n* and its modules.

The received signal at the base station g_1 from sensor node *n* in each UL time-slot is expressed by (3.6) as:

$$x_{g_1,n} = \sqrt{a_{1,n}}x_n + z_{g_1}, n = 1, \dots, N \tag{3.6}$$

where $x_{g_1,n}$ and z_{g_1} are the received signal and the background noise at the base station g_1, respectively, x_n denotes the random signal sensor node *n* transmit which satisfies *E* $[| x_n|^2] = P_n$. The channel capacity of the UL information transfer from sensor node *n* and the base station g_1 is given by (3.7) according to the Shannon's law of channel capacity as [208]:

$$C_n = \beta_n log_2 \left(1 + \frac{P_n a_{1,n}}{\Gamma \sigma^2}\right) \tag{3.7}$$

where β_n denotes the information-transmission time-slot (channel bandwidth) for sensor node *n*, P_n is the average transmit power of sensor node *n*, Γ denotes the signal-to-noise ratio (SNR) gap, σ^2 represents the thermal power noise due to the additive white Gaussian noise (AWGN) from the Shannon's channel capacity. For sensor node *n* information transmission, the maximum achievable throughput in bits/s/Hz (bps/Hz) of sensor node *n* denoted by R_n cannot exceed the channel capacity C_n between the sensor node *n* and the base station g_1 using (3.8) and (3.9), therefore,

$$R_n \leq \beta_n log_2 \left(1 + \frac{P_n a_{1,n}}{\Gamma \sigma^2}\right) \tag{3.8}$$

$$R_n\,(q,\beta) = \beta_n log_2\left(1 + \frac{P_n a_{1,n}}{\Gamma\sigma^2}\right) \tag{3.9}$$

Equation (3.10) is derived by substituting (3.4) and (3.5) into (3.9) as:

$$R_n\,(q,\beta) = \beta_n log_2\left(1 + \alpha_n \frac{\sum_{g=1}^{G} q_g}{\beta_n}\right), n = 1, \dots, N \tag{3.10}$$

where $q = [q_1, q_2, q_3, \dots, q_G]$, $\beta = [\beta_1, \dots, \beta_n]$, α_n denotes the received SNR at the base station g_1 as a result of the information transmitted by sensor node *n* and is expressed by (3.11) as:

$$\alpha_n = \frac{\varsigma_n \eta_n a_{1,n} \sum_{g=1}^{G} P_{A,g}\, b_{g,n} q_g}{\Gamma\sigma^2}, n = 1, \dots, N \tag{3.11}$$

Therefore, the sum-throughput of all sensor node *n* is given by (3.12) as:

$$R_{sum}\,(q,\beta) = \sum_{n=1}^{N} R_n\,(q,\beta), n = 1, .., N \tag{3.12}$$

Network 2: In each given energy harvesting time-slot r_g, according to the TDMA model presented in Figure 3.2, the first time-slot with a length of $0 \leq r_1 \leq 1$ is assigned to a dedicated RF energy source g to transfer energy to sensor node *m* in the DL, while the time allocated to sensor node *m* to transmit its information in the UL to the base station g_1, over channel $f_{1,m}$, is represented with Ψ_m, *m* = 1, 2, …, *M*, with a length of $0 \leq \Psi_m \leq 1$. Therefore, the time allocated to a dedicated RF energy source g to transmit energy to sensor node *m* in Network 2 in the DL and the time allocated to all the sensor nodes *n* to transmit their independent information in the UL is given by (3.13) as:

$$\sum_{g=1}^{G} r_g + \sum_{m=1}^{M} \Psi_m \leq 1 \tag{3.13}$$

The received power at sensor node *m* from a dedicated RF energy source is given by (3.14) as:

$$x_{g,m} = \sqrt{h_{g,m}}\, x_{A,g} + z_m , m = 1, \dots, M \tag{3.14}$$

The amount of energy sensor node *m* harvest in the DL in each time-slot from a dedicated RF energy source g is expressed by (3.15) as:

$$E_{g,m} = \eta_m P_{A,g}\, h_{g,m} r_g , g = 1, \dots, G, m = 1, \dots, M \tag{3.15}$$

Therefore, the total energy sensor node *m* harvest from the dedicated RF energy source g is given by (3.16) as:

$$E_m = \eta_m \sum_{g=1}^{G} P_{A,g}\, h_{g,m} r_g , m = 1, \dots, M \tag{3.16}$$

where η_m is the energy-harvesting efficiency of sensor node *m*, $0 \leq \eta_m \leq 1$, *m* = 1, 2, ..., *M*. It is assumed for convenience that $\eta_1 = \cdots = \eta_M = \eta$. After harvesting energy in the DL phase, a fixed fraction of the energy harvested based on (3.16) is used by each sensor node m to transmit its independent information in the UL to the base station g_1. The average transmit power of sensor node *m*, P_m , is calculated using (3.17):

$$P_m = \frac{\varsigma_m E_m}{\Psi_m}, m = 1, \dots, M \tag{3.17}$$

where ς_m denotes a fixed fraction of the energy harvested used by sensor node *m* to transmit its independent information in the UL to the base station. For the purpose of simplicity, it is assumed that $\varsigma_m = \cdots = \varsigma_M = \varsigma$, while the remaining portion of $1 - \varsigma$ is used for operating the sensor node *n* and its modules.

From (3.16) and (3.17), the channel capacity of the UL information transmission from sensor node *m* and the base station g_1 is given by (3.18) according to the Shannon's law of channel capacity as:

$$R_m\,(r,\Psi) = \Psi_m log_2\left(1+\gamma_m\frac{\sum_{g=1}^{G} r_g}{\Psi_m}\right), m = 1,\dots,M \tag{3.18}$$

where $r = [r_1, r_2, r_3, \dots, r_G]$, $\Psi = [\Psi_1, \dots, \Psi_m]$, Ψ_m denotes the information-transmission time-slot (channel bandwidth) for sensor node *m*, γ_m denotes the received SNR at the base station g_1 as a result of the information transmitted by sensor node *m* and is expressed by (3.19) as:

$$\gamma_m = \frac{\varsigma_m \eta_m f_{1,m} \sum_{g=1}^{G} P_{A,g}\, h_{g,m} r_g}{\Gamma\sigma^2}, m = 1,\dots,M \tag{3.19}$$

Therefore, the sum-throughput of sensor node *m* is given by (3.20) as:

$$\boldsymbol{R_{sum}\,(r,\Psi) = \sum_{m=1}^{M} R_m\,(r,\Psi), m = 1,\dots,M} \tag{3.20}$$

3.5 SUM-THROUGHPUT MAXIMIZATION PROBLEM

To ensure a fair allocation of information-transmission rates between sensor nodes n and m, and to also reduce energy-harvesting unfairness among sensor nodes *n* and *m*, a sum-throughput maximization technique is employed to jointly optimize the energy-harvesting time and the information-transmission rates allocation of sensor nodes *n* and *m*. By so doing, the energy-harvesting efficiency and the information-transmission rates allocation among sensor nodes *n* and *m* are improved. The formulation of the throughput maximization problem is derived from (3.1) and expressed by (3.21) as:

(P1):

$$\max_{q,\beta,r,\Psi} R_{sum}\,(q,\beta) + R_{sum}\,(r,\Psi) \tag{3.21}$$

subject to:

$$\sum_{g=1}^{G} q_g + \sum_{g=1}^{G} r_g + \sum_{n=1}^{N} \beta_n + \sum_{m=1}^{M} \Psi_m \leq 1 \tag{3.22}$$

$$q_g \geq 0, g = 1, \ldots, G \tag{3.23}$$

$$r_g \geq 0, g = 1, \ldots, G \tag{3.24}$$

$$\beta_n \geq 0, n = 1, \ldots, N \tag{3.25}$$

$$\Psi_m \geq 0, m = 1, \ldots, M \tag{3.26}$$

where (3.21) is the objective function, constraints (3.22) represents the energy harvesting and information-transmission time scheduling, (3.23) – (3.26) represent the non-negative constraints for the decision variables. The unknown variables in (P1) are q, β, r, and Ψ. The problem in (3.21) is a non-convex problem due to the *log* function in (3.10) and (3.18). The transformation of the problem to a convex problem was achieved by employing the Lagrangian dual-decomposition method due to its lower complexity. The transformation is described in Addendum A.1. The transformed problem (P1′) can be solved using any convex optimization method. Furthermore, to address energy-harvesting unfairness among the sensor nodes due to the problem transformation, a new problem (P2) is formulated to ensure optimal values of q and r denoted as q^* and r^*. The optimal values of q^* and r^* are used in (P1) to ensure energy-harvesting fairness among sensor nodes n and m. The energy-harvesting unfairness minimization problem is formulated in (3.27) as follows:

(P2):

$$\min_{q^*, r^*} E[(E_n - \bar{E}_n)^2 + (E_m - \bar{E}_m)^2] \tag{3.27}$$

subject to:

$$\sum_{g=1}^{G} q_g + \sum_{g=1}^{G} r_g = 1 \qquad (3.28)$$

$$q_g \geq 0, g = 1, \ldots, G \qquad (3.29)$$

$$r_g \geq 0, g = 1, \ldots, G \qquad (3.30)$$

where $\overline{E}_n$ and $\overline{\boldsymbol{E}}_m$ denotes the minimum energy harvested by sensor nodes n and m. $\overline{E}_n$ is calculated using (3.31):

$$E_n = E(E_n) = \frac{\sum_{n=1}^{N} E_n}{N} \qquad (3.31)$$

$\overline{\boldsymbol{E}}_m$ is calculated using (3.32):

$$E_m = E(E_m) = \frac{\sum_{m=1}^{M} E_m}{M} \qquad (3.32)$$

(P2) depends on variables *q*, and *r*, these variables are yet unknown. To solve for subsequent set of E_n, *n* = 1, ..., *N* and E_m, *m* = 1, ..., *M*, non-zero arbitrary values can be assumed for q_g and r_g. Finding *q** and *r** is achieved as described in the proof for the energy-harvesting unfairness minimization problem, given in Addendum A.2.

Furthermore, a multiple dedicated RF energy source selection algorithm is proposed and used with the sum-throughput maximization method for the multi-network, multi-sensor WIPT system for energy harvesting efficiency and fair information-transmission rate allocations. In Section 3.7, through simulation experiments, the algorithm is shown to be computationally efficient. Moreover, to investigate the information-transmission rate fairness between sensor nodes *n* and *m*, the equation of Jain's fairness index is employed and given by (3.33). According to Jain's fairness equation [209]:

$$J = \frac{\left(\sum_{i=1}^{u} R_u(\delta)\right)^2}{u.\sum_{i=1}^{u}\left(R_u(\delta)\right)^2} \tag{3.33}$$

where $u = n + m$ denotes the summations of sensor nodes n and m, $\delta = (q+\beta)+(r+\Psi)$ denotes the time-length for Network 1, that is, sensor nodes n, and Network 2, that is, sensor nodes m, $R_u(\delta) = R_n(q,\beta) + R_m(r,\Psi)$ denotes the summation of the sum-throughput of Network 1 and Network 2. Also, the worst case and the best case for sensor nodes n and m is defined by $\frac{1}{U} \leq J_{FI} \leq 1$, $\frac{1}{U}$ denotes a minimum fairness rate, while 1 denotes a maximum fairness rate.

3.6 ENERGY HARVESTING AND INFORMATION TRANSMISSION RATE JOINT OPTIMIZATION

Since multiple dedicated RF energy source and multiple sensor nodes are considered in the proposed WIPT system, to address the problem of unfairness in energy harvesting among the sensor nodes and also to improve the information-transmission rates of the sensor nodes, the energy harvesting and the information-transmission timings of the multi-network, multi-sensor, and multi-source WIPT system are jointly optimized so as to increase fairness in the energy harvested from the dedicated RF energy source among the sensor nodes. To achieve this, the proposed Algorithms 1 and 2 are employed to provide optimal energy-harvesting timings and efficient information-transmission rates, thus, maximizing the achievable throughput of the WIPT system. Since the dedicated RF energy source are connected to a controller, Algorithm 1 is implemented at the controller for optimal selection and allocation of the dedicated RF energy source to the sensor nodes in an efficient manner.

Algorithm 1. Selection of dedicated RF energy source and efficient allocation.

Require: $\{n_1, n_2, \dots, N\} >$ sensor nodes n; $\{m_1, m_2, \dots, M\} >$ sensor nodes m;
$\{g_1, g_2, \dots, G\} >$ DRFESs g

Ensure: $q_g^*, r_g^*, g = 1, 2, \dots, \mathrm{G} >$ optimal energy harvesting time

1: for $g = 1{:}\, G$ do

```
  set g to ON
for n = 1: N do
   if g is the nearest to n
      set g to ON and n harvest energy from g using (3.4)
   else
      continue
   end if
end for
  set g to OFF
end for
for g = 1: G do
  set g to ON
for m = 1: M do
   if g is the nearest to m
      set g to ON and m harvest energy from g using (3.16)
   else
      continue
   end if
end for
   set g to OFF
end for
End
```

In the multi-network WIPT system, Algorithm 1 is used to optimally select and switch on and off the dedicated RF energy source. It also considers the number of sensor nodes *n* and *m*, and the available dedicated RF energy source g in the system in each time-slot. Algorithm 1 is responsible for optimally allocating a dedicated RF energy source g to sensor nodes *n* and *m* by firstly considering the nearest dedicated RF energy source g to the sensor nodes, this is important so as to increase fairness in the energy harvested by the sensor nodes from the dedicated RF energy-harvesting sources g in each energy-harvesting phase. Based on the nearness of the dedicated RF energy source to sensor nodes n and m, Algorithm 1 switches a dedicated RF energy source g on in an allocated energy harvesting time-slot. Furthermore, Algorithm 2 is employed to ensure a fair information-transmission rate allocation among sensor nodes *n* and *m*.

Algorithm 2. Efficient information transmission in the UL.

Require: $\{n_1, n_2, \ldots, N\} >$ sensor nodes n;

$\{m_1, m_2, \ldots, M\} >$ sensor nodes m;

$\{g_1, g_2, \ldots, G\} >$ DRFESs g

$gn >$ energized sensor node in n

$gm >$ energized sensor node in m

1: for each gn in n do

2: transfer information in the UL to $g_{1,}$ using (3.5) over $a_{1,n} = 10^{-3} d_{g,n}^{-\rho}, g = 1, 2, \ldots, G\ n = 1, 2, \ldots, N$

3: end for

4: for each gm in m do

5: transfer information in the UL to $g_{1,}$ using (3.17) over $f_{1,m} = 10^{-3} d_{g,m}^{-\rho}, g = 1, 2, \ldots, G, m = 1, 2, \ldots, M$

6: end for

End

3.7 SIMULATION EXPERIMENTS AND DISCUSSION

The multi-network WIPT system configurations are selected from the simulation parameters in Table 3.1. The configuration of the multi-network WIPT system includes sensor nodes *n* and *m*, contained in Network 1 and Network 2, respectively. The dedicated RF energy source g in the WIPT system are deployed in a predetermined manner in an illustrative environment of 21 m by 21 m. One of the dedicated RF energy source is randomly selected as the base station for the UL, assumed to be at a fixed distance, D_{UL}, from both the networks. Since there is a channel reciprocity in Network 1 and Network 2 in the DLs and in the ULs, we assume the channel model of $a_{g,n} = b_{g,n} = 10^{-3} d_{g,n}^{-\rho}, n = 1, 2, \ldots, N$ for Network 1, and $f_{g,m} = h_{g,m} = 10^{-3} d_{g,m}^{-\rho}, m = 1, 2, \ldots, M$ for Network 2, where $d_{g,n}$ stands for the distance between sensor node *n* and the dedicated RF energy source g in meters, $d_{g,m}$ stands for the distance between sensor *m* and the dedicated RF energy source g in meters, and ρ denotes the path loss exponent.

Table 3.1. Assumed simulation parameters

Parameter	Value
Transmission power of the dedicated RF sources	3000 mW
Noise power	−114 dBm
Energy-harvesting efficiency	0.5
Fraction of energy used for information transmission	0.5
Signal-to-noise gap	1.5
RF transceiver frequency	915 MHz
Bandwidth	1 MHz
Path loss exponent	2
Medium access control	IEEE 802.15.4

The same simulation parameters have been assumed in the SNMSMS work described in [204], which was used as a state-of-the-art baseline for comparing the results obtained in the proposed multi-network, multi-sensor, and multi-source of this work. The performance of the new work is extensively analyzed in MATLAB and compared with the existing baseline work in [204].

An example multi-network, multi-sensor, and multi-source simulation with five dedicated RF energy source could, for instance, produce coordinates of (8.1 m, 2.9 m) for g_1 , (2.1 m, 2.2 m) for g_2, (5.3 m, 2.9 m) for g_3, (10.2 m, 2.9 m) for g_4, and (15.3 m, 2.2 m) for g_5. For the purpose of showing the coordinates of the dedicated RF energy source, an example of a network structure is given in Figure 3.3.

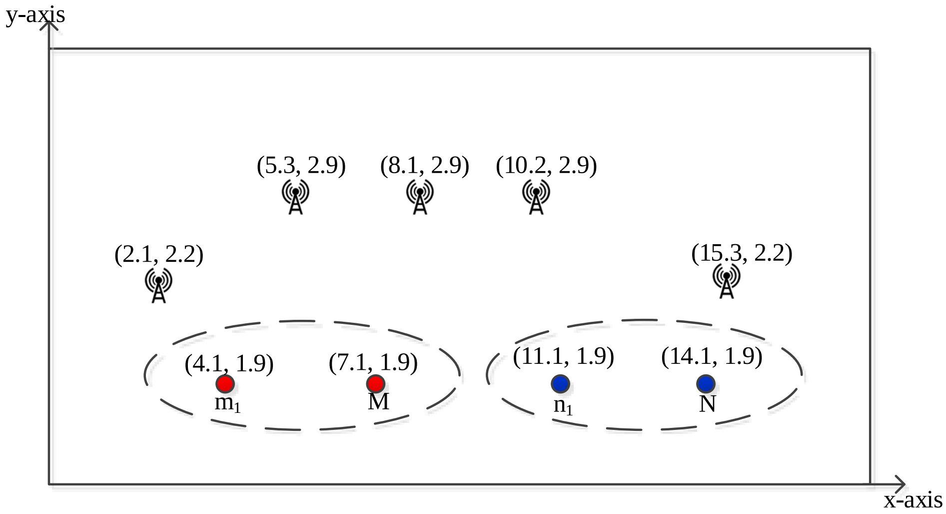

Figure 3.3. Example of a network structure

3.7.1 Results and discussion

The proposed algorithms presented in Section 3.6 were implemented for simulation experiments on the proposed multi-network, multi-sensor, and multi-source system for various configuration instances, while evaluating the achievable average sum-throughput and the fairness of the resulting system. In each run, the system considered the number of sensor nodes and the number of the dedicated RF energy source as input parameters. For each simulation experiment, the total number of sensor nodes n and m was denoted by k (i.e. $k = n + m$). Also, for each run, different placements of the networks n and m were efficiently generated by considering the nearest dedicated RF energy source to the sensor nodes for optimal allocation. In order to compare the proposed WIPT system with the existing state-of-the-art system in [204], a total number of sensor nodes k equal to two and three were considered for different numbers of dedicated RF energy source, ranging between one and five. The simulated results are generated through MATLAB, and the run times of the simulations are 500.

3.7.1.1 Effect of run time on the system-achievable sum-throughput and fairness

Ensuring convergence of the optimization algorithms for efficiently finding and allocating the best dedicated RF energy source for energy harvesting is important, and therefore the effect of the runtime on the system outputs are considered. Figure 3.4 shows the average achievable sum-throughput rate, of the system depending on the total number of simulation runs. Both Algorithms 1 and 2 were activated for all simulation runs. For these runs a two-sensor system (i.e. k equal to two) and a three-sensor system (i.e. k equal to three) configurations are used, while the number of dedicated RF energy source were varied, to a maximum of five. It was established from Figure 3.4 that a larger number of simulation runs improved the system throughput rate of a two-sensor system with a maximum difference of only 0.3%, and a three-sensor system with a maximum difference of 0.3%. This is an indication that the two-sensor system and the three-sensor system have the same rate of convergence, due to the number of the sensor nodes in the optimization problem. From these results, it can be deduced that averaging the system outputs over 500 runs provide reasonable results. The simulated results between 10 and 200 run times are almost similar, and as depicted in Figure 3.4, the proposed solutions saturate to optimal points between 200 and 500 run times, which indicates that the solutions are capable of efficiently handling a large number of sample set within a short and reasonable time frame. For the purpose of consistency with the state-of-the-art systems, 500 run times are used as a baseline. Also, solving the optimization problem by the proposed solutions has a lower complexity and takes about 0.060 s per each run, which is lower compared to the more complex existing solution, which requires about 1 s per each run due to its exhaustive search method. The computer system employed for running the simulations uses an AMD E1-1200 processor running at 1.40 GHz and with 4 GB RAM specifications.

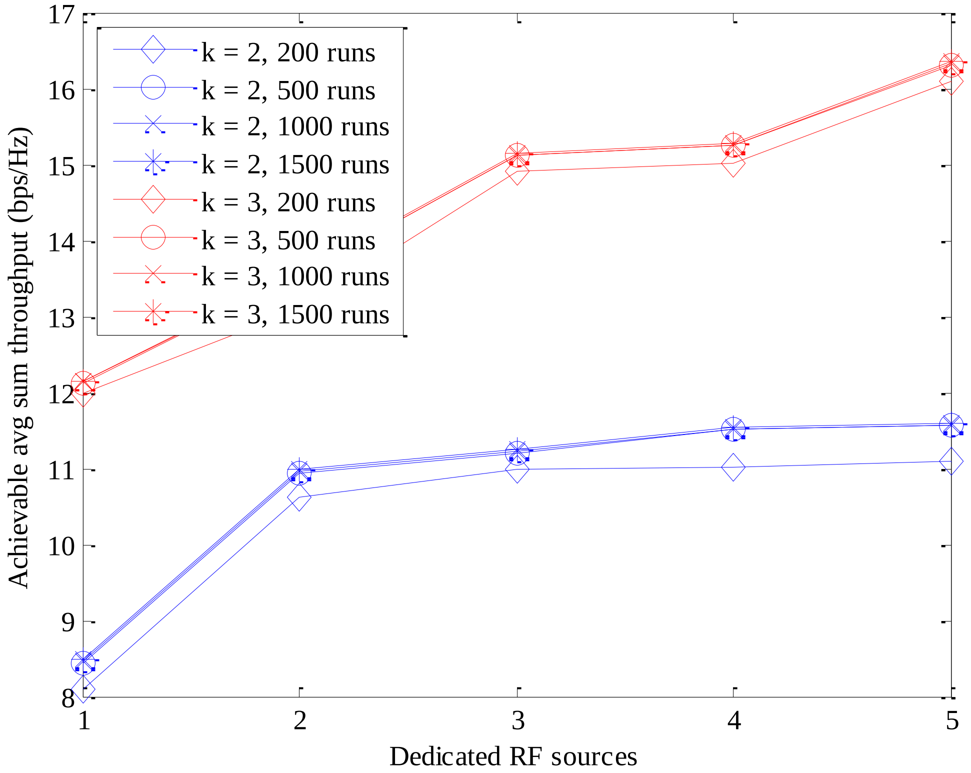

Figure 3.4. The impact of run time on the average system-achievable sum-throughput. The blue lines indicate a 2-node network, while the red lines indicate a 3-node network.

3.7.1.2 Effect of network distance from the base station on the system-achievable sum-throughput

This section studies the effect of the distance of networks to the base station on the achievable sum-throughput rate in a two-sensor system (i.e. *k* equal to two) and a three-sensor system (i.e. *k* equal to three) powered by five power sources over an average of 500 run times. The achievable average sum-throughput of the system slightly deceases as the distance of the networks from the base station increases, as shown in Figure 3.5. This establishes that the rate at which the system throughput decreases with distance is small for the systems with *k* equal to two and *k* equal to three. The performance gains of both *k* equal to two and k equal to three systems in this experiment slightly improved for short distances in contrast to the k equal to two and k equal to three systems in Figure 3.4, and the different optimal placements of the networks n and m that were efficiently generated by considering the nearest dedicated RF energy source to the sensor nodes by the proposed solutions have as well contributed to the improvements.

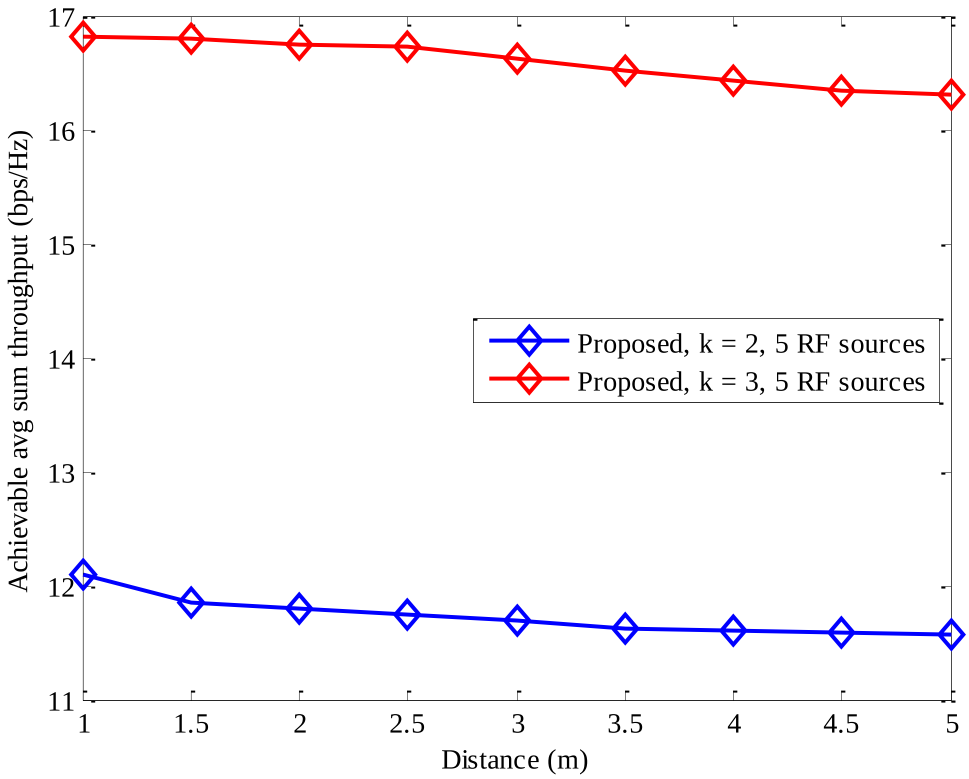

Figure 3.5. The impact of different networks distance from the base station on the system-achievable throughput rate. The blue lines indicate a 2-node network, while the red lines indicate a 3-node network.

3.7.1.3 Comparison of sum-throughput and fairness performance for different system configurations

Simulation experiments were performed on the proposed multi-network, multi-sensor, and multi-source system and the existing single-network, multi-sensor, and multi-source

(SNMSMS) system for various configuration instances, where the results included the achievable average sum-throughput and the fairness of the systems. In each run, the system considered the number of sensor nodes and the number of the dedicated RF energy source as input parameters. For each simulation experiment, the total number of sensor nodes n and m was denoted by k. Also, for each run, different placements of the networks n and m were efficiently generated by considering the nearest dedicated RF energy source to the sensor nodes for optimal allocation. Both Network 1 and Network 2 are considered at a distance of 5 m to the base station. Each simulation experiment was averaged over a run of 500 instances in time. Figure 3.6 describes the achievable average sum-throughputs of the proposed multi-network WIPT system and the single-network WIPT system, while Figure 3.7 presents the fairness of the multi-network and the single-network systems. The multi-network, multi-sensor, and multi-source system produced a better achievable sum-throughput and fairness value than the existing single-network, multi-sensor, and multi-source system. The improvements are due to the efficient selection and allocation of the dedicated RF energy source using Algorithms 1 and 2. For example, when k is set to two with one dedicated RF energy source, the multi-network, multi-sensor, and multi-source system produced an average sum-throughput of 8.44 bps/Hz and a fairness index of 0.992, while the data published in [204] for the single-network, multi-sensor, and multi-source system are an average sum-throughput of 6.18 bps/Hz and a fairness index of 0.876. These results represent significant improvements of 36% in the system throughput rate, and 13% in the fairness index. Also, when k is set to three with a dedicated RF energy source of one, the multi-network, multi-sensor, and multi-source system produced an average sum-throughput of 12.11 bps/Hz and a fairness index of 0.992, while the published data for the single-network, multi-sensor, and multi-source system are an average sum-throughput of 10.07 bps/Hz and a fairness index of 0.876 [204]. These results represent significant improvements of 20% in the system throughput rate, and 13% in the fairness index.

Also, the results conform with the mathematical analysis in (3.4), (3.5), (3.10), (3.16)–(3.18), because the system throughput is influenced by the amount of energy harvested by the sensor nodes. As shown in Figure 3.7, the problem of the doubly near–far condition between sensor nodes in the existing WIPT systems was efficiently handled by Algorithms 1 and 2 through the increase in the influx of dedicated RF power sources to the proposed system. Furthermore, the fairness results presented in Figure 3.7 for the proposed system significantly improved compared to the fairness of the existing state-of-the-art system. This was as a result of the quality channel experienced in the proposed system, where the static wireless channels between the dedicated RF energy source and the sensor nodes are always constant, and this has favoured the fair allocation of energy harvesting time and information-transmission rate to each sensor node in the network. Consequently, the overall system throughput rate and fairness rate are improved.

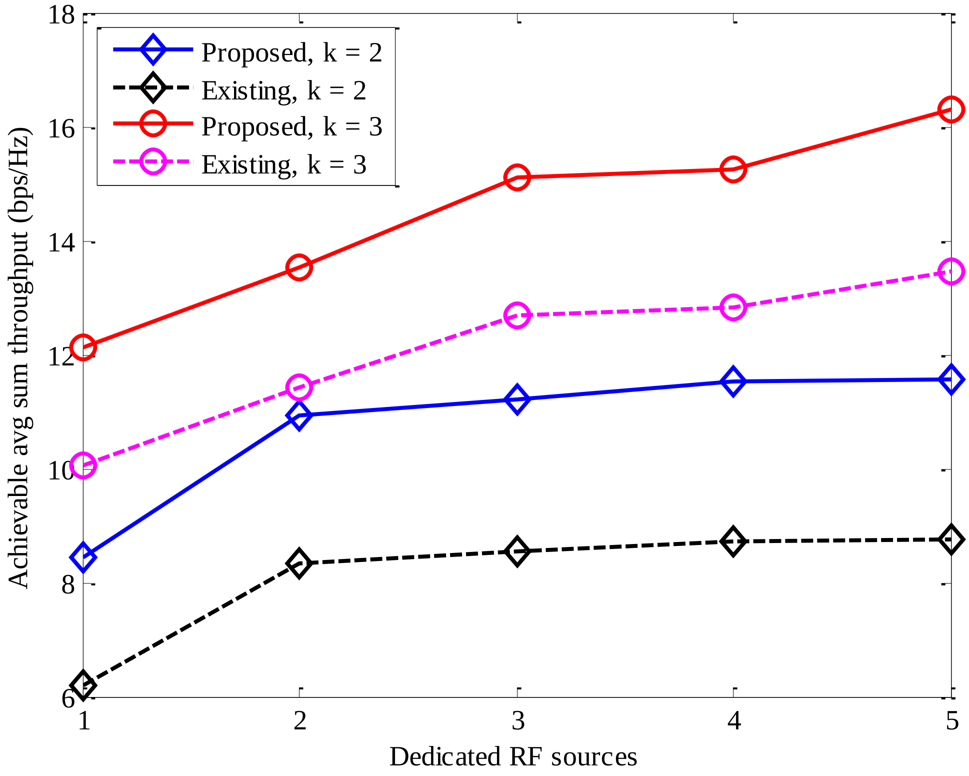

Figure 3.6. Achievable average sum-throughput against number of dedicated RF sources. The blue lines indicate a 2-node network, while the red lines indicate a 3-node network. The solid lines represent the proposed, while the dashed lines represent the existing system [204].

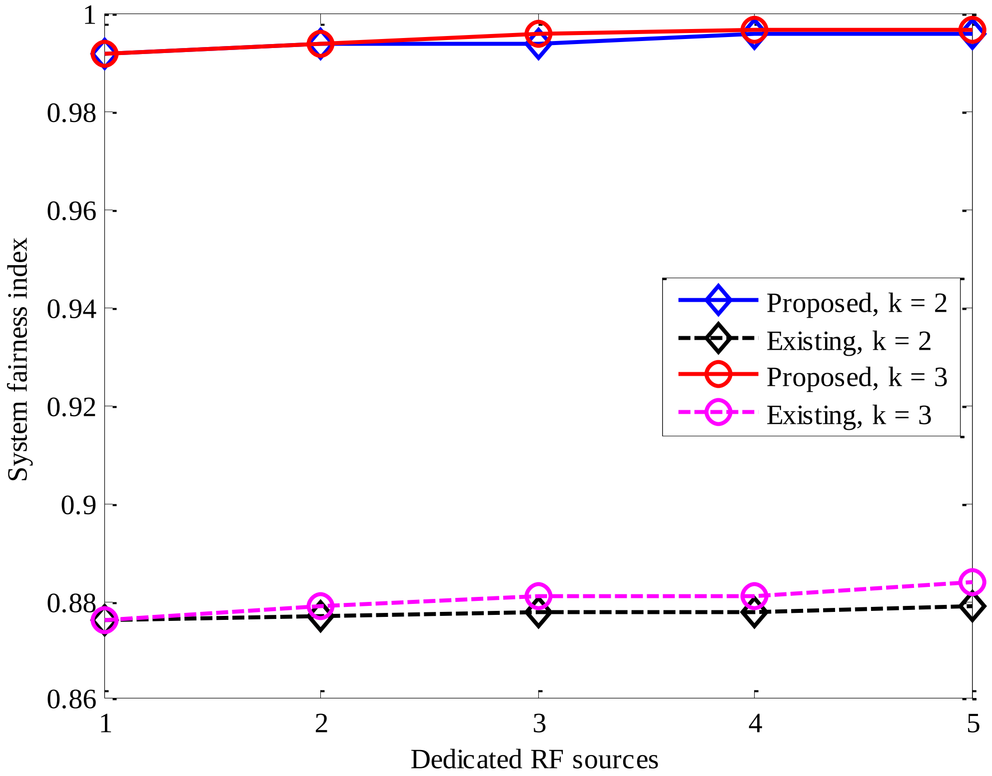

Figure 3.7. System fairness index against number of dedicated RF sources. The blue lines indicate a 2-node network, while the red lines indicate a 3-node network. The solid lines represent the proposed, while the dashed lines represent the existing system [204].

3.7.1.4 Comparison of the system performance dependent on network distance from the base station

This section investigated the effect of networks distance in the UL, D_{UL}. To achieve this, an equal distance among two groups of network in the multi-network, multi-sensor, and multi-source was considered. One network simulation was considered at a distance of 4.5 m to the base station, while another network simulation was considered at a distance of 5.5 m to the base station in a WIPT system with three sensor nodes, and powered by five 3W dedicated RF energy source. As shown in Figure 3.8, the difference in the network distance slightly influenced the system-achievable throughput rate. This decrease is due to the system wireless channel conditions. Consequently, the distance of a network to the base station in a multi-network, multi-sensor, and multi-source WIPT system contributes to the achievable throughput rate of the system.

The results obtained were also compared with the existing state-of-the-art WIPT system to further emphasize the contributions of the proposed algorithms. The average difference between the throughput rates as a function of D_{UL} of the multi-network, multi-sensor, and multi-source and single-network, multi-sensor, and multi-source are 1.4% and 1.6% for distances 4.5 m and 5.5 m. This is an indication that the multi-network, multi-sensor, and multi-source system has a better rate of convergence compared to the single-network, multi-sensor, and multi-source system, due to the efficiency of Algorithms 1 and 2 in handling fairness in energy harvesting and information-transmission rate allocation. Figure 3.9 presents the system fairness index. Once again, average fairness difference with distance of the multi-network, multi-sensor, and multi-source and single-network, multi-sensor, and multi-source are 0.2% and 0.6%. This is due to the efficiency of Algorithms 1 and 2 in ensuring fairness among the sensor nodes in the multi-network, multi-sensor, and multi-source system.

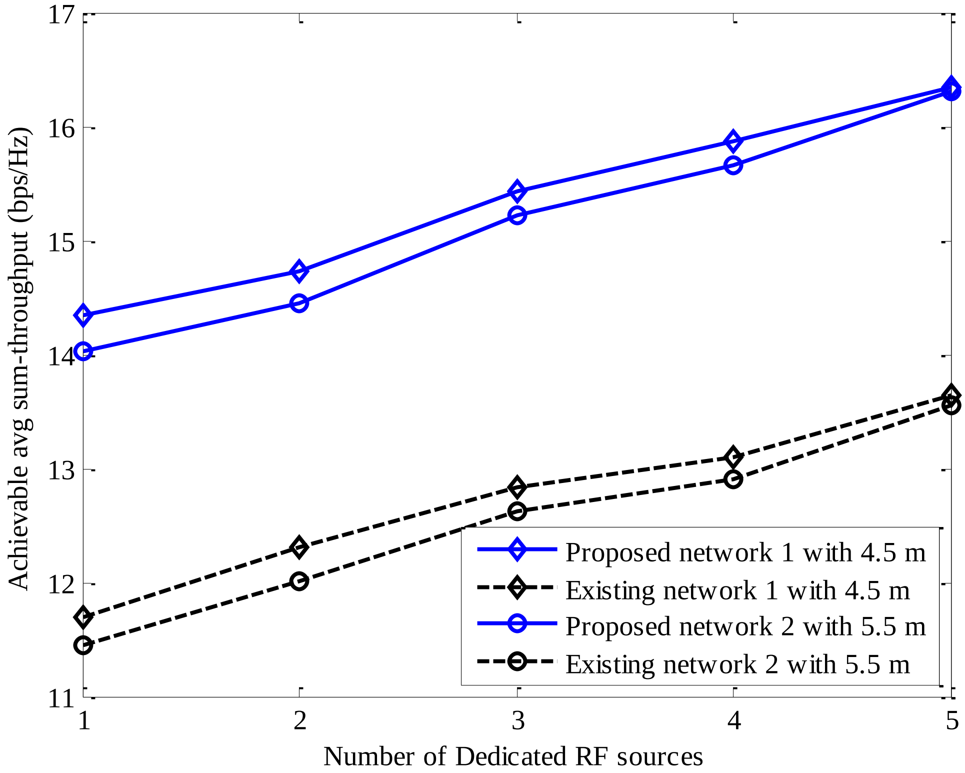

Figure 3.8. The impact of different network distance D_{UL} on the system-achievable throughput rate. The solid blue lines indicate the proposed systems, while the dashed black lines represent the existing systems [204].

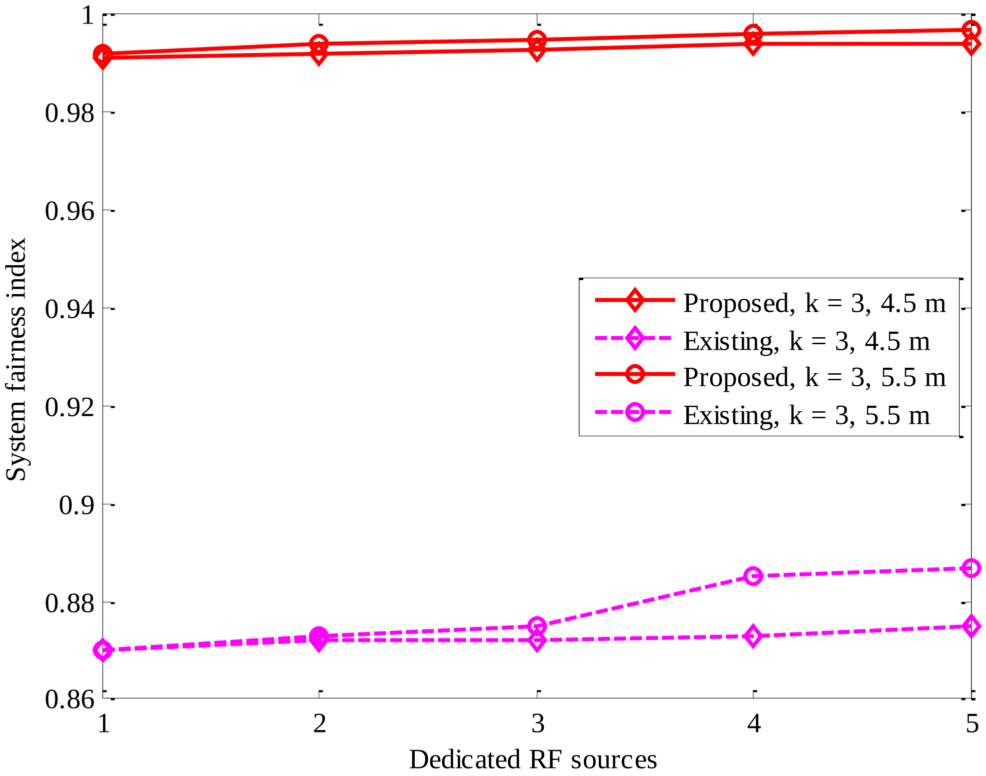

Figure 3.9. The impact of different network distance D_{UL} on the system fairness index. The solid red lines indicate the proposed systems, while the dashed magenta lines represent the existing systems [204].

3.7.1.5 Effect of transmission power on the system-achievable sum-throughput

The effect of different transmit power on the system's achievable sum-throughput rate is investigated in Figure 3.10. The system is configured with *k* equal to 2 and powered by four dedicated RF energy source. The transmit power of the dedicated RF energy source is set to 200 mW, 300 mW, 400 mW, and 3000 mW. Based on the different values of transmit power, a significant increase in the system's throughput rate was observed as the transmit power of the dedicated RF energy source was increased from 200 mW, 300 mW, 400 mW to 3000 mW. This is an indication that the transmit power of the dedicated RF energy source directly influences the performance of the system. From the result, it can be observed that even for transmit power as low as 200 mW, the achieved throughput rate result is adequate, which means that the proposed system is energy-efficient for sustainable network communications.

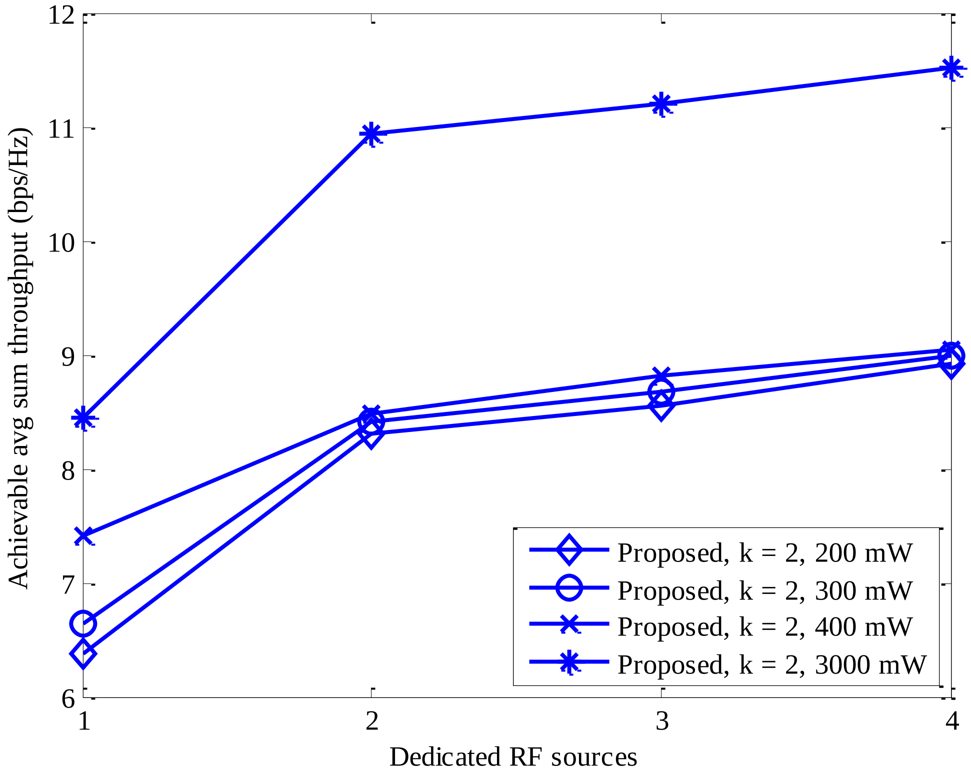

Figure 3.10. The impact of transmit power on the system-achievable throughput rate. The solid blue lines indicate the proposed systems.

3.8 CHAPTER SUMMARY

This chapter has provided a solution to the problem of unfairness in energy harvesting and unequal information-transmission rate allocation, also known as the doubly near–far problem, in a multi-network, multi-sensor and multi-source WIPT system in a static environment by studying efficient resource allocation for increased system performance. To achieve this, new efficient optimization algorithms were proposed. The proposed algorithms have revealed improved and interesting throughput rate and fairness results compared to the existing state-of-the-art algorithm. The newly proposed system provided a better fairness index among the sensor nodes in the system, and a great transmission throughput rate. The newly proposed algorithms had improvements of 36% in the system throughput rate, and a fairness index of 13% for a two-sensor system. These results represent significant improvements in the system throughput rate and fairness index. Also, the proposed WIPT system is energy-efficient, and ensures sustainable communication.

For emphasis purposes, it is worthy of note that this chapter has addressed the need for predetermined deployment of WQ sensors in a water monitoring environment settings for energy efficiency, including efficient use of network resources to minimize to consumption of network energy resources and also enhance the network throughput for optimal communication of the system WQ information. Also, a new TDMA-based scheme was proposed energy efficient communication in the network. To cater for different energy efficient deployment strategies, network heterogeneity, efficient utilization of network resources (such as energy and time-slot) and an efficient communication protocol powered by a new TDMA scheme, a new solution model is presented in Chapter 4.

CHAPTER 4 EFFICIENT ENERGY RESOURCE UTILIZATION IN A WIRELESS SENSOR NETWORK FOR WATER QUALITY MONITORING

4.1 CHAPTER OVERVIEW

In this chapter, a new approach to energy harvesting and data transmission optimization in a heterogeneous-based multi-class and multiple resource wireless transmission wireless sensor network system that focus on monitoring water and its quality, is presented. The overview of each section in this chapter are provided as follows. In Section 4.2, the need for efficient sensing systems for WQM to guard against the devastating impact of unclean water on the ecosystem is presented. Also, in this section, the problem of energy scarcity, and a sustainable energy solution for combating the problem are presented. In Section 4.3, important concepts, fundamental problems such as unfairness issues, and the related works are discussed. The key contributions of the chapter are also presented in this section. In Section 4.4, a multi-class, multiple-intended-source (MCMIS) wireless powered sensor network (WPSN) system for WQM application, is designed, and Section 4.5 presents the mathematical models for the new WQM system. In Section 4.6, a sum-throughput maximization problem is designed to reduce the system energy consumption and enhance the system overall throughput rate. The throughput optimization problem is formulated as a non-convex function. Through the exploitation of the problem structure, it is converted to a convex function. The mathematical models of the optimization problem are validated through numerical simulations. In Section 4.7, an efficient allocation algorithm for energy and information transmission scheduling is designed, while results and discussion are presented in Section 4.8. The chapter summary is presented in Section 4.9.

4.2 BACKGROUND

In recent times, there has been an upsurge in the need for efficient sensing systems for monitoring the parameters of WQ that include bacteria load and pH values, in a timely fashion [1], [210]. Most times, E. coli is considered as an indicator organism for microbiological analysis of water [211-213]. The main reason for the upsurge in seeking efficient sensing systems is because of the devastating impact of unclean water on human, plant, and animal. The systems are intended to complement the existing traditional systems for effective monitoring of water and its quality, in order to combat the problem of contamination in water [1], [210], [214]. Across the globe, an approximate estimate of two-hundred and fifty million cases of disease caused by polluted water is reported annually [62]. These diseases are responsible for human death and claims up to about ten million lives across the globe annually [62]. This is an indication that water problems caused by contaminants are major issues in this dispensation. The alarming rate of human death on a global scale caused by water pollution is as a result of a surge in water and environmental contaminants. These contaminants are due to two major factors, namely natural processes and man-made (anthropogenic) activities [1], [3], [215]. Examples of natural phenomena that adversely influence the quality of water through climatic factors are run-off caused by hydrological conditions, rock weathering, soil leaching, depositions caused by wind, and evapotranspiration, while some of the key man-made activities that negatively influences the quality of water are mining operations, deforestation, agricultural run-off, and industrial effluent [216].

As a result of the surge in water contaminants, water consumed from either the water polluted by natural processes or man-made activities is dangerous to humans and the ecosystem, because of their high levels of heavy metals and microbes. The microbes and heavy metals cause havoc to human health. Examples of some of the disruptions they cause are diarrhea, epigastric pain, organ damage such as renal and hepatic failure, and cancer [4], [5]. For example, around one million five hundred thousand children die due to diarrhea every year [217]. Heavy metals are highly toxic and also create a lot of environmental concerns [1], [6], [7], [8]. To address these issues, there is an urgent need for effective systems for frequently monitoring WQ parameters. To achieve this, the adoption of wireless sensor network technology has been proposed as a promising solution. Unfortunately, wireless sensor networks are faced with several challenges that range from energy, memory, and processing capability. As a result of these limitations, both academia and industry are currently making efforts toward seeking solutions to the aforementioned problems. Among the issues raised in wireless sensor networks, the energy scarcity problem is the greatest of all, as the operation of other modules depends on energy [53], [29]. The problem of energy scarcity in wireless sensor networks has been in existence for a long time on the account of the limited energy budget of the batteries that are typically used for powering the sensor nodes in wireless sensor network systems [1], [115]. To meet the objective of wireless sensor network-based WQM systems in the context of timely monitoring without interruption in energy supply, harvesting energy from energy sources, which is technically referred to as energy harvesting technique in practice is a promising approach [1], [218]. The technique has been exploited by the energy harvesting research community in wireless sensor networks to replace the utilization of battery power, which is associated with several problems that include short life span, cost of battery replacement, and difficulty in battery replacement. Energy harvesting from sources that include solar [1], [71], RF signals [1], [219], [90], and wind [91], have been exploited. However, the most interesting energy source among the above-mentioned sources is RF energy harvesting from intentionally stationed power sources [1]. The main reason for this is that energy harvesting from intended RF power sources (IPS) is controllable, as well as suitable for continuous monitoring of water distribution networks

[99]. Similarly, energy harvesting from IPS is suitable for energy transmissions over larger areas because of its far-field characteristics of energy radiation [99]. As a consequence of the benefits of energy harvesting from IPS, it is an attractive energy solution for water monitoring applications in enclosed environments, although the energy solution can be employed in any location.

At the moment, there are commercial IPS solutions [220]. This development is as a result of the advances in wireless energy transmission technology. One of the leading energy solution providers is Powercaster®. Forms of RF transmitters from Powercaster® are the battery-powered IPS [221], and the TX91501 IPS [221]. They are reliable solution for transferring RF energy in a wireless manner and they can cover a distance of about 24 m. They are compatible with the unlicensed bands of the industrial, scientific and medical (ISM) model for communications [222]. In addition, the Powercaster® energy solutions come with a compatible RF harvester, which is employed at the sensor node for energy harvesting.

Recently, an RF energy harvesting method based on wireless energy transmission and wireless information transmission (WPN) has emerged as a promising solution for powering sensor nodes in wireless sensor networks. The technique is suitable for conveying the signals of the sensor nodes to a local base station. Such a system is typically referred to as a sensor network that is based on wireless powering (WPSN). With this WPN technique, abundant RF energy could be efficiently transferred from an IPS to a large number of sensor nodes in a network to achieve a stable supply of energy without any interruption in communication that may result due to energy depletion [99], [120].

In this chapter, WPN and network heterogeneity concepts are investigated seek solutions to energy problems, sustainable wireless sensor network system with an unwavering quality-of-service (QoS) experience in the context of optimal throughput, stable energy supply, and unfairness issues.

4.3 RELATED LITERATURE

Currently, the recent works on WPSN solutions considered energy harvesting from a single IPS for sensor nodes powering, while only few have exploited the utilization of multiple IPS. In [128], for example, an investigation was carried out on a WPSN application powered by a single IPS. The IPS was employed to wirelessly recharge the batteries of the network sensor nodes. Also, they considered the optimization of the harvesting of energy and the transmission of information timing schedules, to address the effect of unfairness on information transmission rates. Due to a single IPS solution considered in the work, the sensor nodes in the network suffers from a doubly far-near problem as the sensor nodes that are nearer to the deployed IPS receives more energy compared to the sensors that are far away. Consequently, unfair information transmission rates are experienced by the sensors when this problem is encountered in the network. To improve fairness in information transmission rates among the network sensor nodes, a common-throughput technique was explored and exploited. However, the common-throughput technique is complex and is not a reflection of a practical scenario. The unfairness issues in the energy received and the information transmission rate among the network sensor nodes are addressed in this chapter by exploring a heterogeneous multi-class and multiple resource wireless transmission system.

Likewise, in [223] a single IPS-based WPSN system is considered to study the trade-off in the throughput of communication channels. To achieve this, two modes of communication that include half-duplex and full-duplex are employed, and consequently the network devices may operate in any of the modes adopted. To study trade-off in throughput in the DL and UL regions, two receiver architectures, namely power-splitting and time switching, were integrated to the network sensor node, while new communication protocols were proposed based on the combination of the communication mode and the receiver architecture. However, the proposed WPSN system suffers from the inherent interference problem that faces full-duplex systems.

An exploration is performed in [202] of the concept of self-recharging of sensor nodes in a network system powered by an IPS. The study exploited a full-duplex mode of communication in a co-located energy transmitter and information receiver architecture that transmits/receives over an in-band frequency such that the energy transmitter and the information receiver carries out their communications over a single frequency band in a simultaneous fashion. The employed communication mode may be advantageous in improving the spectral efficiency of the operating frequency, however, it suffers from interference problems as the energy transmitter that co-locates with the information receiver causes a complex co-channel interference issue. Since full-duplex communication allows simultaneous communications, the sensor nodes in the full-duplex system in [202] performs data transmission and energy reception concurrently. The network sensor nodes also perform self-recharging as they transfer their independent information. These processes make the system complex as the network sensor nodes are faced with a strong self-interference that causes corruption of data transmissions. Interference cancellation techniques are employed, however, it is difficult to achieve perfect cancellation of self-interference in a wireless channel. The interference issues in turn affect the system’s overall performance in terms of energy efficiency and achievable throughput rate. The complexity associated to the work in [202] is circumvented in this chapter by exploring a half-duplex communication mode in both co-located and separated energy transmitter and information receiver architectures operating in separate time-slots over a single frequency band. The employed technique in this chapter is cost-effective and alleviates the problem of interference faced by the full-duplex approach operating in in-band. The application of both co-located and separate energy transmitter and information receiver architectures employed in this chapter tackles the practical doubly near-far issue faced by the co-located architecture adopted by [202].

A WPSN system for healthcare application is investigated in [203]. The healthcare application was powered by an IPS, and new strategies are proposed for the optimization of the sensor signal transfer rate to the network access point. The study explored two cases that include abnormal and normal situations for transmissions under two schemes, namely time switching and power splitting. For example, the exploration of the abnormal transmission was investigated at the network sensor node under the time switching scheme, while a normal transmission was studied at the network sensor node using the power splitting scheme.

The utilization of multiple IPS is investigated in [204], which considered the optimization of the harvesting of energy and the transmission of information timing schedules of a WPSN system for an on-body application in a dynamic environment. The proportion of the time-period earmarked to harvesting for an individual IPS to recharge a sensor node was calculated, which is a function of the movement of the object carrying the sensor nodes. This work did not consider network heterogeneity, as different network specifications are key for a practical system and optimal utilization of resources. The limitation is catered for in this chapter to develop a more practical system.

In [224], the optimization of an energy harvesting based wireless sensor network system powered by an IPS is considered. The essence of the work is to investigate the maximization of the sum-throughput of the sensors contained in the network with respect to their individual information communication throughput requirement. However, this work is limited by the available energy resource and consequently undermines the potential of the network sensor nodes in meeting their required information transfer rate due to the inherent hardware doubly near-far condition in wireless powered wireless sensor network systems. This phenomenon is addressed in this work through the deployment of multiple energy resources, which potentially power the network sensor nodes, regardless of their distances, to meet their required information transmission rates.

In [27], the optimization of a WPSN system information transmission and energy harvesting timing schedules was investigated in a joint fashion. The deployment of the sensors in the network was predetermined to target some strategic positions, allowing the control of distances of the sensor nodes to the available IPS. This facilitates fairness in the context of the distances among the sensor nodes to the available energy resources. As a result, equal optimal energy harvesting timing is earmarked to individual sensor nodes for energy harvesting. This work did not consider random deployment of sensors, giving scope for the consideration of network heterogeneity to cater for a more real-world situation in this chapter. Unlike the predetermined deployment scenario in [27], in this work sensor nodes are classified based on their distance specifications using the heterogeneity concept.

In this work, a new WPSN is proposed. For efficient resource allocation, and to also realize a more practical system, network heterogeneity is considered. Heterogeneous wireless sensor networks are class of networks where sensor nodes have different properties in terms of distance specification and resources allocation. More often, wireless sensor networks are treated as homogeneous, whereas, in real scenarios the networks may have different properties. Consequently, realistic wireless sensor networks may not be achieved in homogeneous sensor networks. Heterogeneity is a key design consideration for the realization of efficient and workable systems that are capable of solving several needs. Therefore, the concept of heterogeneous networks is employed in this work to classify sensor nodes based on their distance specifications and deployment strategy. As a consequence, a multi-class network is formed, containing Class A and Class B networks. Class A network sensor nodes are distributed in a predetermined manner to meet some specific design goals, while the sensors in Class B are deployed in a random pattern. It is essential to emphasize that in the proposed heterogeneous networks, the considered sensor nodes are heterogeneous in nature in terms of their capability to harvest different energy as well as use different energy transfer protocols due to the introduced network requirements in terms of different distance specifications and different deployment strategy that have orchestrated the development of heterogeneous-based communication protocols used by the network nodes to speak to themselves.

Different from [204], equal optimal energy harvesting time is provided to the sensor nodes in Class A network because of their nearness to the IPS, while a new parameter T_{EH} is introduced to allot different energy harvesting periods to Class B sensors based on their distance from the IPS. Based on the new harvesting time period parameter, an optimal shorter time is allotted to the Class B sensors that are near to the IPS, while an optimal larger time is allotted to the Class B sensors that are far from the IPS in the DL. Moreover, to achieve similar signal communication rates within the sensor nodes in the UL, the sensors which are considered far from the BS are allocated a longer information transmission time to ensure that they have enough time to transfer their separate signals. To achieve this, a new algorithm is proposed to achieve efficient allocation of optimal harvesting time to individual sensors based on their class of network, in order to enhance the system overall throughput rate.

Most often, the time-multiplexing receiver model is employed in WPSN systems because of its installation simplicity, portability, and suitability for efficient harvesting of energy from RF signals [99], [204], [224]. Unfortunately, the current WPSN solutions which are developed based on time-multiplexing are confronted with a number of issues when there are no efficient strategies in place [204]. Such issues range from unfairness in energy harvesting time allocation, interference problems caused by energy transmission in the context of multiple IPS, to unequal information communication rates within the sensors in a network [225], [201]. A multi-class, multiple-intended-source WPSN system is proposed for monitoring the quality of water in water stations, to address the above-mentioned issues. Also, this chapter is intended to ensure that individual sensors in the network are efficient enough to obtain adequate energy for delivering their acquired signals with the desired QoS. The major contributions of this chapter are fourfold as highlighted below:

- A new communication scheme that employs TDMA is developed to efficiently solve the wireless energy and information transmission scheduling problem.

- The optimization of the DL time and the UL time for energy and information transmissions are achieved with the new TDMA scheme in a joint fashion, to enhance the system overall throughput rate.

- Optimal allocation of energy resources to the heterogeneous sensor nodes based on their class of network.

- A new algorithm is developed to improve fairness in resource allocation between the sensor nodes in different classes of a heterogeneous wireless sensor network.

This chapter is divided into the following sections: Section 4.4 presents the structure of a sensor node devoted to monitoring WQ and expounds the proposed multi-class, multiple-intended-source WPSN system architecture and the proposed TDMA protocol for the system. The proposed model for the new system wireless channel is described in Section 4.5. Section 4.6 presents the optimization of the energy and information transmissions rate problem, while an efficient algorithm for multiple IPS allocation and information transmission timing in Section 4.7. The discussion of the proposed WPSN system sum-throughput and fairness results are considered in Section 4.8, which validate the formulated sum-throughput optimization problem. The conclusion of the chapter is contained in Section 4.9.

4.4 METHODOLOGY

4.4.1 Sensor node hardware design for monitoring water quality

In this section, a simple overview of the building blocks of a sensor node for monitoring WQ parameters. The WQ sensors are portable, but powerful tools used for monitoring the microbial and the chemical parameters of WQ at water stations. An integral component of a WQ sensor is the communication technology. Communication technologies can be classified into two categories, namely local communication technology and remote communication technology. The local communication technology is used to connect a sensor to another sensor, as well as a BS. The remote communication technology is responsible for delivering WQ information to a remote center. The remote communication technology acts as an internet gateway in the network. An internet gateway simply means an internet access point via which the system is connected to the internet.

The WQ sensors are made up of four essential modules, namely sensor, micro-controller, power supply and communication. The sensor module is used for measuring the desired parameter of WQ in the form of analog information, and converting the measured information into a digital form through an analog-to-digital converter (ADC). For the realization of real water quality sensors, off-the-self sensors can be purchase as well a customized water quality sensor can be employed for this experiment.

The micro-controller module is responsible for the coordination of the processes that integrates the sensor module with other modules in a way to execute instructions that relates to the measurements of the sensor module. Other key functions carried out by the micro-controller involves the collection of the information measured by the sensor unit, storing of the gathered measurements in its storage chip, and transferring of the information collected using the communication technology of the communication module to a BS.

The communication module is important in the WQ sensor node architecture as it provides a suitable platform for WQ information transmission, and reception of important control signals. The communication module is usually implemented as an RF transceiver. The RF transceiver is equipped with an antenna, and has the capabilities for both information transmission and reception. The CC2420 ZigBee radio is an example of a communication technology for local information transmission, and is defined in the IEEE 802.15.4 specification [226]. The ZigBee radio is considered suitable to be employed in this work because of its low-cost and low-power features. Each of the ZigBee-based WQ sensors communicates directly with a local BS over the license-free ISM bands (such as 2.4 GHz and 915 MHz). Through a remote communication technology employed at the BS, which acts as a gateway to the internet (such as 2G, 3G, or LTE networks), the WQ information received from the sensors is delivered to the remote monitoring stations [1].

The power supply section is a crucial unit in WQ sensor node architecture as it provides energy within the node for powering different modules. The power supply unit may be composed of key devices like an energy harvester and a battery. In this work, an RF-based energy harvester from Powercaster® (for example the P2110 device) [227] is considered, and incorporated in the power supply unit for harvesting RF energy from an IPS to recharge the WQ sensor in-built batteries. The RF energy harvester works by converting the RF energy received from an IPS into electrical energy through an RF-to-DC converter. The energy is suitable for powering the sensor node. The integration of the described real components of water quality sensors make the implementation of real sensor nodes realistic and achievable. A typical structure of a wireless sensor network system that employs WQ sensors devoted to the monitoring a body of water and its quality is presented in Figure 4.1.

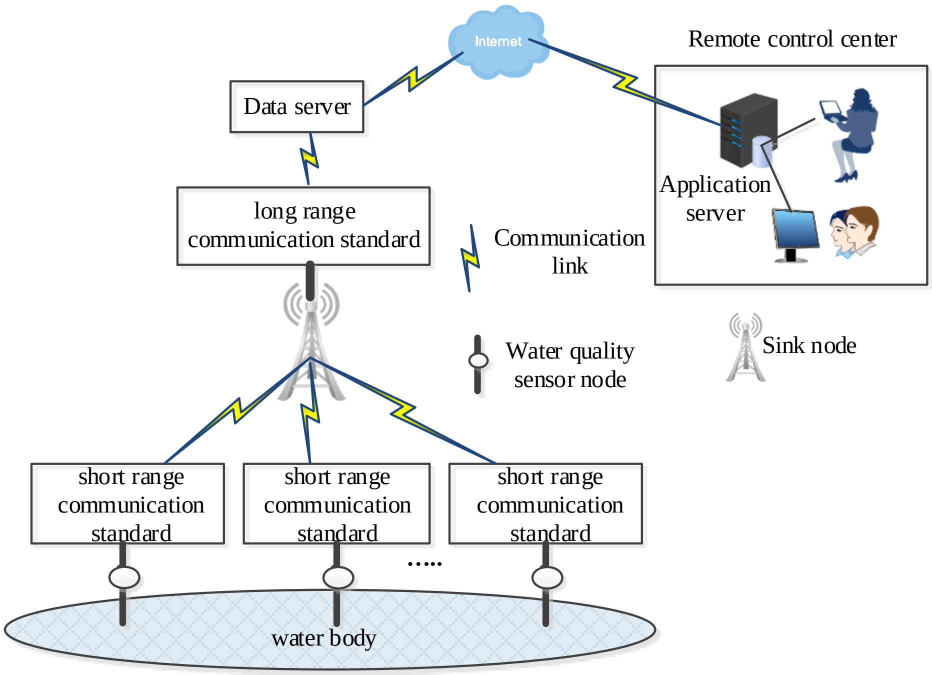

Figure 4.1. A typical WQM system model.

4.4.2 System architecture design

In the system architecture, a WPSN system powered by intended RF power sources (IPS) is considered. The system contains two classes of heterogeneous networks. Let the WQ sensors

a in Class A be denoted by $a \in \{a_1, a_2, .., A\}$, while the WQ sensors b in Class B is denoted by $b \in \{b_1, b_2, .., B\}$. Also, a set of IPS represented by $c \in \{c_1, c_2, .., C\}$ are distributed in the system at specified positions. To provide sufficient energy for powering the WQ sensor nodes, more IPS devices are deployed. The sensor nodes a in Class A are distributed in a determined fashion to target some strategic locations, while the sensors in Class B are deployed in a random manner, as presented in Figure 4.2. The main essence of the two classes of network considered in this study is to cater for several needs, for example the enhancement of effective monitoring of different parameters of WQ such as pH and E. coli.

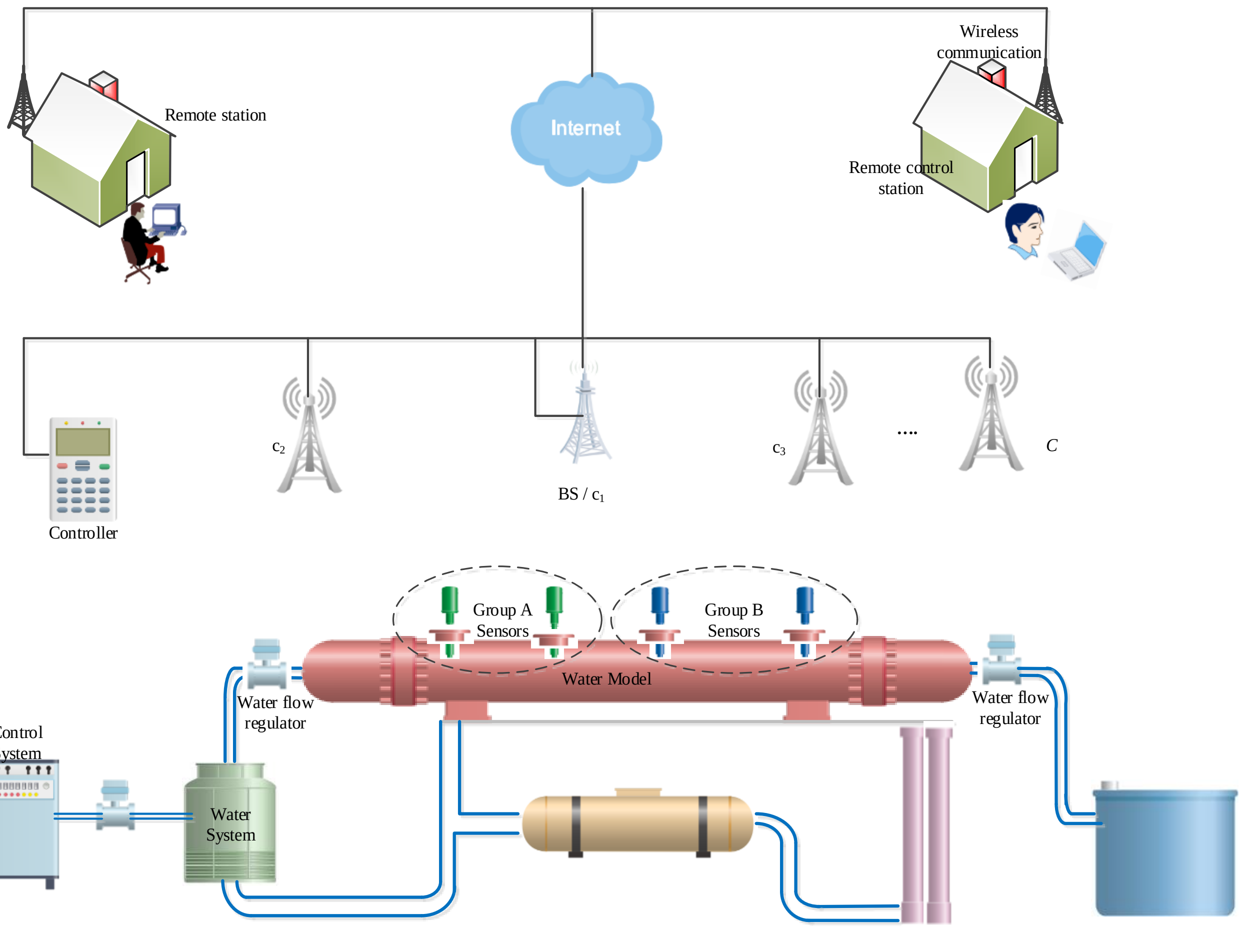

Figure 4.2. Proposed model for WQM in a water processing station.

The multi-class approach employed in this work helps to properly classify the sensor nodes based on their distance specifications and deployment strategy, as depicted in Figure 4.2. The IPSes are employed to achieve wireless transmission of energy to the sensors contained in the two classes of network during the DL phase, while only c_1 has the capability for both wireless energy transmission and wireless information reception in the DL and UL phases. In addition, it is equipped with an internet access capability for remote delivery of WQ information to water control centers. A controller is employed to connect the IPSes, controlling their operation based on the newly proposed TDMA protocol, which circumvents any occurrence of interference in energy transmissions. The new TDMA protocol is given in Figure 4.3. The controller switches the available IPSes on and off at a calculated time, in a sequential manner. To create a suitable platform for the sensors deployment, a section for monitoring the quality of water, which allows constant water flow is designed as in [1], [207], [228]. The water body that is scheduled for monitoring is pumped to the designed water section in an enclosed location.

In the system architecture, the sensor nodes a in Class A are provided with equal optimal energy harvesting time, because of their nearness to the IPS. Unlike the sensor nodes in Class A, there are different distances within the sensor nodes in Class B because of the random approach employed for their deployment. Therefore, there may be some significant variations in the energy a sensor node in Class B is able to harvest in a DL-EH block. This situation is an inherent issue in WPSNs that is typically referred to as the doubly-near-far problem. When this problem is encountered in a network, the energy that a particular sensor node which is not far from a BS is able to harvest is significant compared to the energy that another sensor node which is far from the BS is able to harvest. This can be attributed to the condition of the wireless channels. To tackle the doubly-near-far issue in this chapter, unlike the same optimal energy harvesting time that is allotted to Class A sensors, different optimal energy harvesting time is provided to the individual sensors in Class B. In addition, in the UL stage, an optimal information communication period is provided to Class A sensors, as well as Class B sensors, based on their distances to the BS, to ensure completeness in the transmission of their individual information to the BS. To achieve this, in each information transfer block, the distances to the BS of the sensor nodes a and b in Classes A and B, respectively, are considered, and based on this distance an optimal time is allotted to an individual sensor to transfer its individual information. The new TDMA protocol described here is summarized in Figure 4.3.

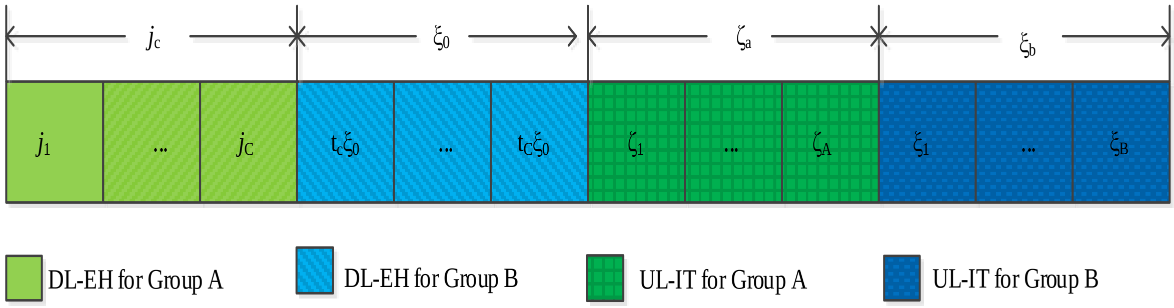

Figure 4.3. Proposed TDMA scheme.

4.5 WIRELESS CHANNEL MODEL

The environment of the application is assumed to be a static environment. As a result, the wireless channels between the sensor nodes and the IPS c, are modelled using a quasi-static fading model. The channels that connect the sensor nodes a and b to the BS, are denoted with complex variables or complex channel gains $\tilde{m}_{c,a}$ and $\tilde{g}_{c,b}$ in the UL phase, for classes A and B, respectively. While the reversed channels that go from an IPS to the sensor nodes a and b, are denoted with $\tilde{n}_{c,a}$ and $\tilde{u}_{c,b}$ in the DL phase, for classes A and B. Consequently, the channel power gains for the two classes are derived as $m_{c,a} = |\tilde{m}_{c,a}|^2$ and $n_{c,a} = |\tilde{n}_{c,a}|^2$ for Class A, and $g_{c,b} = |\tilde{g}_{c,b}|^2$ and $u_{c,b} = |\tilde{u}_{c,b}|^2$ for Class B. For clarity purposes, note that the channel power gains are represented by the square of the modulus of the complex variables, while the first order norm $(i.e, L^1 - norm)$ or the absolute value of the complex variables are utilized as in references [128] and [224].

In addition, each IPS is assumed to have knowledge of the channel state information (CSI), and as a result employs the CSI knowledge to ensure the transmission of optimal energy to individual sensors in the two classes in an adaptive fashion.

The proposed multi-class, multiple-intended-source WPSN system is further described as follows:

Class A:

In a particular j_c period, with the application of the TDMA protocol in Figure 4.3, an energy harvesting time of $0 \leq j_c \leq 1$, $j_c \geq 0, c = 1, \ldots, C$, is allotted to an IPS c to send energy via the DL channels to sensors a, while the scheduled time for sensor nodes a for transferring their signals over channel $m_{1,a}$, to BS / c_1 in the UL phase, is represented with time period ζ_a, $a = 1, 2, \ldots, A$, with a length of $0 \leq \zeta_a \leq 1$. Therefore, the time allocated to an IPS c for energy transmission to the sensor nodes in Class A, and the scheduled time for the sensor nodes to communicate their separate signals in the UL phase, is given in (4.1) as:

$$\sum_{c=1}^{C} j_c + \sum_{a=1}^{A} \zeta_a \leq 1 \tag{4.1}$$

In (4.2), the amount of power that a sensor node receives from an IPS is formulated as:

$$x_{c,a} = \sqrt{n_{c,a}} x_c + z_a, \ \forall\, a = 1, 2, \ldots, A \tag{4.2}$$

where $x_{c,a}$ means the power signal received by senor a, and z_a indicates the background noise at a as a result of the energy received from an IPS c. x_c denotes the arbitrary complex random signal of an IPS c that satisfies $E[|x_c|^2] = P_c$, where P_c means the IPS c transmission power, and is assumed large enough that the background noise at a is insignificant as a consequence.

In the DL phase, the energy a sensor node a harvests from an IPS c, in a given time-slot, is formulated in (4.3) as:

$$E_{c,a} = \varepsilon_a P_c\, n_{c,a} j_c, \forall\, c = 1,2, \ldots, C, \forall\, a = 1,2, .., A \tag{4.3}$$

Moreover, the overall energy received by sensor node a from the IPS c is modelled in (4.4) as:

$$E_a = \varepsilon_a \sum_{c=1}^{C} P_c\, n_{c,a}\, j_c,\ \forall\, a = 1,2, \ldots, A \tag{4.4}$$

where ε_a denotes the efficiency of the RF-to-DC converter module of sensor node a and is defined as $0 \leq \varepsilon_a \leq 1$, for a=*1,2,…,A.* The assumption is made that $\varepsilon_1 = \cdots = \varepsilon_A = \varepsilon$, for simplicity sake.

To optimize the energy consumption of each sensor node a, only a fraction of the energy obtained by each of them in (4) is allowed to be consumed for information transmission. Consequently, an average transmission power is defined for the sensor nodes as modelled in (4.5) as:

$$P_a = \frac{\Psi_a E_a}{\zeta_a}, \forall\, a = 1, \ldots, A \tag{4.5}$$

In (4.5), P_a is the average transmission power defined for a sensor node a., while Ψ_a indicates the fixed value allowable part of the energy available to a to transfer information to the BS. Ψ_a is defined as $\Psi_a = \cdots = \Psi_A = \Psi$, for convenience. It is important to mention that,$1 - \Psi$, which is the remaining fraction of the harvested energy, is utilized for operating the internal modules of a sensor node a.

The received signal at the BS c_1 from individual sensors a in each UL time-slot is given by:

$$x_{c_1,a} = \sqrt{m_{1,a}}\, x_a + z_{c_1}, \forall\, a = 1, \dots, A \tag{4.6}$$

where $x_{c_1,a}$ means the signal received by the BS c_1, x_a denotes an arbitrary random signal of a sensor node a that satisfies $E[|x_a|^2] = P_a$, and z_{c_1} is used to denote the background noise at c_1 as a result of the signal received from a sensor node a. For the transmission of information in the UL by sensor a to c_1, the capacity of the channel is defined as (4.7), based on Shannon's law [208]:

$$D_a = \zeta_a log_2\left(1 + \frac{P_a m_{1,a}}{\Gamma\sigma^2}\right) \tag{4.7}$$

In (4.7), the signal transfer time (related to the channel bandwidth of the system) is denoted with ζ_a, the SNR gap is represented with Γ, and the noise power is represented with σ^2. The maximum throughput that sensor a can achieve in b/s/Hz is represented with R_a and is defined in (4.8) as:

$$R_a \leq \zeta_a log_2\left(1 + \frac{P_a m_{1,a}}{\Gamma\sigma^2}\right) \tag{4.8}$$

By substituting (4.5) and (4,4) into (4.8), the throughput rate can be derived in the form of

$$R_a\ (j, \zeta) = \zeta_a log_2\left(1 + \alpha_a \frac{\sum_{c=1}^{C} j_c}{\zeta_a}\right), \forall\, a = 1, 2, \dots, A \tag{4.9}$$

where $j = [j_1, j_2, j_3, \dots, j_C]$, $\zeta = [\zeta_0, \zeta_1, \dots, \zeta_a]$, and α_a represents the SNR at c_1 and is defined in (4.10) as:

$$\alpha_a = \frac{\Psi_a\, \varepsilon_a m_{1,a}\, \sum_{c=1}^{C} P_c\ n_{c,a} j_c}{\Gamma\sigma^2}, \forall\, a = 1, ., A \tag{4.10}$$

Consequently, for all the of sensors a, the sum-throughput is defined in (4.11) as:

$$R_{sum}\ (j,\zeta)=\sum_{a=1}^{A} R_a\,(j,\zeta),\ \forall\ a=1,2,..,A \tag{4.11}$$

Class B:

In Class B, an optimal energy harvesting time with a length of $0 \leq t_1\xi_0 \leq 1$ is calculated and allotted to an IPS c to transmit energy to each individual sensor b over the DL communication channels, while an optimal period of time ξ_b is apportioned to a sensor b to communicate its signal through the UL links to c_1 over a channel $g_{1,b}$. The apportioned time ξ_b, *b = 1, 2, …, B,* has a length of $0 \leq \xi_b \leq 1$. Therefore, the time period apportioned to an IPS c for the transmission of energy, and also the time period apportioned to sensor nodes b for communicating their different signals to the BS, is formulated in (4.12) as:

$$\sum_{c=1}^{C} t_c\,\xi_0 + \sum_{b=1}^{B} \xi_b \leq 1 \tag{4.12}$$

The amount of power that a sensor node receives from an IPS is formulated as:

$$x_{c,b}\ =\ \sqrt{u_{c,b}}x_c\ +\ z_b\,,\forall\ b=1,2,\dots,B \tag{4.13}$$

In the DL phase, the energy a sensor node b harvests from an IPS c, in a given time-slot, is formulated in (4.14) as:

$$E_{c,b}\ =\varepsilon_b P_c\,u_{c,b}t_c\xi_0,\forall\ c=1,2,\dots,C,\forall\ b=1,2,..,B \tag{4.14}$$

The total energy received by sensor node b from the IPS c is modelled in (4.15) as:

$$E_b\ =\varepsilon_b\sum_{c=1}^{C} P_c\,u_{c,b}\,t_c\xi_0,\ \forall\ b=1,2,\dots,B \tag{4.15}$$

Once again, it is assumed for convenience that $\varepsilon_1 = \cdots = \varepsilon_B = \varepsilon$.

From (4.15), a part of the energy obtained by each sensor b is consumed for information communication in the UL phase and is formulated in (4.16) as:

$$P_b = \frac{\Psi_b E_b}{\xi_b}, \forall\, b = 1, 2, \dots, B \tag{4.16}$$

where P_b is the average transmission power defined for a sensor node b, while Ψ_b indicates the allowable part of the energy contained in b for information communication to the BS, which is fixed. Ψ_b is defined as $\Psi_b = \cdots = \Psi_B = \Psi$, for convenience. The rest of $1 - \Psi$ is utilized for operating the modules of a sensor node b.

The received signal at c_1 from individual sensors b in each UL time block is:

$$x_{c_1,b} = \sqrt{g_{1,b}}x_b + z_{c_1}, b = 1, \dots, B \tag{4.17}$$

The attainable throughput rate in b/s/Hz of sensor node b is defined as:

$$R_b\ (t, \xi) = \xi_b log_2\left(1 + \gamma_b \frac{\sum_{c=1}^{C} t_c \xi_0}{\xi_b}\right), \forall\, b = 1,2,..,B \tag{4.18}$$

where $t = [t_1, t_2, t_3, \dots, t_C]$,$\xi = [\xi_0, \xi_1, \dots, \xi_b]$. γ_b is the SNR received at c_1, which is caused by the transferred information from sensor node b. It is defined in (4.19) as:

$$\gamma_b = \frac{\Psi_b\ \varepsilon_b g_{1,b} \sum_{c=1}^{C}\ P_c u_{c,b} t_c}{\Gamma\sigma^2}, \forall\, b = 1,..,B \tag{4.19}$$

Hence, for all of the sensors b the sum-throughput is defined in (4.20) as:

$$R_{sum}\ (t, \xi) = \sum_{b=1}^{B} R_b\ (t, \xi), \forall\ b = 1, 2, .., B \tag{4.20}$$

4.6 MAXIMIZATION OF ATTAINABLE THROUGHPUT

The maximization of the WPSN system attainable throughput is described in this segment. To achieve this, a sum-throughput optimization strategy is employed. Based on the optimization technique, the timing schedules for the harvesting of energy and transmission of information by sensor nodes a and b were optimized in joint fashion. With this, an improved fairness in the allocation of harvesting timing, including fairness in the rates of the sensor nodes information transmission, is achieved. Consequently, an enhanced system overall throughput rate is achieved with minimal energy consumption. The general representation of the system attainable throughput is formulated as a maximization problem in (P3). From (4.1), we have:

(P3):

$$\max_{j,\zeta,t,\xi}\ R_{sum}\ (j, \zeta) + R_{sum}\ (t, \xi)\ + ... + R_{sum}\ (s, \upsilon) \tag{4.21}$$

subject to:

$$\sum_{c=1}^{C} j_c + \sum_{c=1}^{C} t_c\, \xi_0 + \sum_{a=1}^{A} \zeta_a\ + \sum_{b=1}^{B} \xi_b \leq 1 \tag{4.21a}$$

$$j_c \geq 0, \forall\ c = 1, 2, .., C \tag{4.21b}$$

$$t_c \geq 0, \forall\ c = 1, 2, .., C \tag{4.21c}$$

$$\zeta_a \geq 0, \forall\, a = 1, 2, .., A \tag{4.21d}$$

$$\xi_b \geq 0, \forall\, b = 1, 2, .., B \tag{4.21e}$$

The objective function of the optimization problem is given in (4.21), while the constraints of the optimization problem are (4.21a) to (4.21e). Constraint (4.21a) is the timing schedules for energy harvesting and information transmission. The non-negative constraints (4.21b), (4.21c), (4.21d), and (4.21e) are defined for the decision variables, while variables j, t, ζ, ξ are unknown in (P3). The maximization problem in (P3) is a non-convex problem since (4.9) and (4.18) contain a log function. By exploiting the structure of the problem, variable $t_c\xi_0$ is changed to $\xi_{0,c}$, and the natural log form of the log function is obtained. They are substituted in (4.9) and (4.18) respectively. Based on this development, the optimization problem in (P3) is transformed to a convex problem. The newly generated problem from the original problem is defined as (P4). The proof for the new problem is provided in Addendum B1. Consequently, the newly transformed problem is solvable by employing any standard convex approach [1], [206].

Moreover, in order to provide a solution to unfairness in energy harvesting as a result of the transformation, we formulated a new problem as (P5) to guarantee the optimality of j and t, which is indicated as j* and t*. Consequently, these values (j* and t*) are employed in (P3). The formulation of the minimization problem for addressing the unfairness in energy harvesting among the sensors is expressed in (4.22) as:

(P5):

$$\min_{j^*, t^*} E[(E_a - \bar{E}_a)^2 + (E_b - \bar{E}_b)^2] \tag{4.22}$$

s.t:

$$\sum_{c=1}^{C} j_c + \sum_{c=1}^{C} t_c = 1 \tag{4.22a}$$

$$j_c \geq 0, \forall\ c = 1, 2, .., C \tag{4.22b}$$

$$t_c \geq 0, \forall\ c = 1, 2, .., C \tag{4.22c}$$

In (4.22), the minimum energy received by a and b is defined by $\bar{E}_a$ and $\bar{E}_b$, and is calculated based on (4.23) and (4.24).

$$E_a = E(E_a) = \frac{\sum_{a=1}^{A} E_a}{A} \tag{4.23}$$

$$E_b = E(E_b) = \frac{\sum_{b=1}^{B} E_b}{B} \tag{4.24}$$

(P4) is contingent to variables *j*, *t*, ξ_0, which are unknown. To determine the intermediate harvested energy for E_a, *a = 1, 2…, A*, as well as E_b, *b = 1, 2…, B*, arbitrary values could be used for j_c and ξ_0. The proof for determining optimal *j** and t* is provided in Addendum B2.

In addition, to handle multiple IPS allocation in an efficient manner to ensure fairness in harvesting and signal transmission rates among Class A and Class B sensors, an efficient algorithm is developed. Moreover, to determine the rates of fairness in resource allocation and signal transmission in the system, the concept of Jain's fairness index [27], [229] is employed, as expressed in (4.25).

$$JF = \frac{\left(\sum_{k=1}^{v} R_v\ (\beta)\right)^2}{v.\sum_{k=1}^{v}\left(R_v\ (\beta)\right)^2} \tag{4.25}$$

In (4.25), $v = a + b$, which represents the complete network of sensors in classes A and B. $\beta = (j + \zeta) + (\xi)$ is the combined time length for classes A and B sensor nodes. While, the overall aggregate of the sum-throughput of Class A and Class B is defined by $R_v(\beta) =$

$R_a(j,\zeta)$+ $R_b(\xi)$. For the sake of performance measurement, the best case, as well as the worst case, of the overall sensor nodes in Class A and Class B, is expressed by (4.26) as:

$$\frac{1}{V} \leq JF \leq 1 \tag{4.26}$$

According to (4.26), 1 indicates a maximum fairness ratio, while $\frac{1}{V}$ means a minimum fairness ratio.

4.7 EFFICIENT ALLOCATION ALGORITHM FOR ENERGY AND INFORMATION TRANSMISSION SCHEDULING

In this section, an efficient resource allocation algorithm is presented and is defined as Algorithm 3. The essence of the proposed algorithm is to ensure fairness in EH-DL timing schedules among the system sensor nodes. In addition, it is aimed to achieve an enhanced rate of information transfer among the network sensor nodes in the UL. To achieve this, the proposed algorithm optimizes the energy and information transfer timing schedules in a joint fashion, according to the mathematical models presented in Section 4.5 such that optimal time periods are allocated for both energy harvesting and information transmission to classes A and B in the network. As a consequence, Algorithm 3 optimally allots an IPS c to individual sensor nodes for at a calculated optimal time period. In a similar vein, to make sure that the sensors in the network are provided with sufficient time for communications in the UL phase, an optimal information transmission time period is calculated and allotted. The implementation of the algorithm is done on the system controller to achieve the optimal control of the switching of the IPS and optimally allocating them to the sensors for enhancing the attainable throughput of the WPSN system.

Algorithm 3. Optimization algorithm for efficient resource allocation (OAERA)

Require: $\{a_1, a_2, .., \mathrm{A}\}, \{b_1, b_2, .., \mathrm{B}\}$ > sensor nodes a and b ; $\{c_1, c_2, .., \mathrm{C}\}$> IPS c

Ensure: j_c^* , t_c^*, $\forall\ c = 1,2 \dots, \mathrm{C}$ > optimal energy harvesting time

ζ_a^* , ξ_b^*, $\forall\ a = 1, 2 \dots, \mathrm{A}$, b= 1,2 … , B > optimal information transfer time.

DL timing schedule for energy harvesting

1. Initialization:

2: Let $c \leftarrow 1{:}C$ for $a \in \{a_1, a_2, .., A\}$

3: switch c to ON for $0 \leq j_c^* \leq 1$

4: for $a = 1{:}\ A$ do

5: check for the closest c and allocate to a

6. if c is the closest to a then

7. allocate c to a ,and energy is transferred for an optimal assigned time period using the energy model in (4.4) and $n_{c,a} = 10^{-3} d_{c,a}^{-\omega}$

8. otherwise continue with the search

9. end if

10. end for

11. switch OFF c

12: Let $c \leftarrow 1{:}C$ for $b \in \{b_1, b_2, .., B\}$

13: switch c to ON for $0 \leq t_c^* \leq 1$

14: for $b = 1{:}\ B$ do

15: find the distance between b and the available c's

16: with the calculated distances, allocate optimal (short or large) DL-EH time to b and harvest energy from c using the energy model in (4.15) and $u_{c,b} = 10^{-3} d_{c,b}^{-\omega}$

17: end for

18. switch OFF c

UL timing schedule for information transmission

19: for $a = 1: A$ do

20: switch ON c_1 for $0 \leq \zeta_a^* \leq 1, \forall\, a = 1, 2, .., A$

21: find the distance between a and c_1

22: with the calculated distance, allocate optimal (short or large) UL-IT time to a and the models in (4.8) and (4.9) are employed for the transmission of sensor a information to the BS c_1 , and (4.5) calculates the average energy consumed by sensor a for transmitting information

23: switch OFF c

24: end for

25: for $b = 1: B$ do

26: switch ON c_1 for $0 \leq \xi_b^* \leq 1, \forall\, b = 1, 2, .., B$

27: find the distance between b and c_1

28: with the calculated distance, allocate optimal (short or large) UL-IT time to b and the models in (4.18) and (4.19) are employed for the transmission of sensor b information to the BS c_1 , and (4.16) finds the average energy consumed by sensor b for transmitting information

29: switch OFF c

30: end for

end

To analyze the complexity or performance of the OAERA algorithm, two key parameters used for characterizing the complexity of an algorithm are employed in this study. The parameters are the time complexity and space complexity. Note that the analysis of the time complexity of an algorithm involves the required time to execute an algorithm of a particular size n, while the analysis of the space complexity is concerned with the required system resources (such as memory) to execute an algorithm of a particular size n. To achieve the characterization of the complexities of the OAERA algorithm, Big-O (O) notation is applied. The time complexity of the OAERA algorithm is $O(A(C+1)+2B)$. Consequently, the computational time complexity of the algorithm is linear in sensor nodes in A and B, and directly proportional to the IPS C. The space complexity of the OAERA algorithm is $O(A+B+C)$, which reveals a linear complexity. These indications show that the OAERA algorithm has efficient complexities in the context of time and space. An algorithm with a linear complexity is better than an algorithm with an exponential complexity as in [204] since the efficiency of $n > 2^n$. Also note that algorithms with exponential complexities are solvable, but not tractable. As a result, they may explode. An exponential-time complexity consumes more time and space resources compared to algorithms with linear complexities, and polynomial time complexities defined by n^q where $q \geq 2$, such as quadratic complexity and cubic complexity. It is important to underline that system resources can efficiently take care of linear-time and polynomial-time algorithms as they are solvable and tractable.

4.8 RESULTS AND DISCUSSION

This section presents the performance of the proposed optimization algorithm is evaluated in MATLAB environment by investigating the effects of number of sensors, path-loss exponent, and transmission power on the system, through simulation experiments. In addition, the system performance is verified in a comparative manner in the context of the number of IPS available in the system, and Jain's fairness ratio. Also, to further substantiate the contributions of this work, two networks at unequal distances to the BS are investigated, to showcase the improvement in network performance. Based on simulation experiments, the computational efficiency of the proposed optimization algorithm is shown, while the simulation settings presented in Table 4.1 are employed to configure the proposed WPSN system. This work assumes similar network parameters as in a recent reference work [204], for comparison purposes.

Table 4.1. System parameters

Parameter	**Value**
Carrier bandwidth	1 MHz
SNR	1.5 dB
Noise power	-114 dBm
IPS transmission power	3000 mW
Efficiency of RF energy conversion	0.5
Channel path-loss exponent, ω	2.0
Allowable portion of energy for information transfer	0.5
MAC layer	IEEE 802.15.4
Operating frequency	915 MHz
Path-loss channel model	$n_{c,a} = m_{c,a} = 10^{-3} d_{c,a}^{-\omega}$
Path-loss channel model	$u_{c,b} = g_{c,b} = 10^{-3} d_{c,b}^{-\omega}$

The implementation of the algorithm was done on the following proposed WPSN system. Two classes of network are considered at a distance of 3 m apart. In Class A, a distance of 6 m is considered for the placement of one or two sensor nodes by taking the data in the reference work into consideration. In Class B the WQ sensors are distributed at a random distance of 2.5-4 m from each other – as typical in monitoring the quality of water. In addition, it is possible to vary the distance among the sensor nodes. Furthermore, it is worth mentioning that during optimization different strategic positions are considered for the IPSes.

4.8.1 Algorithm convergence based on iteration number

In this experiment to investigate the convergence of the system, both the number of sensors and IPSes in the network are fixed, while the number of iterations is changed during the simulation. Figure 4.4 depicts the convergence of the proposed OAERA algorithm in the context of attainable system sum-throughput per sensor nodes against iteration number. For this experiment, a system configured with 2 sensors and a system configured with 3 sensors were investigated. The two systems are powered by 5 IPS, which is consistent with the reference work [204]. From Figure 4.4, it can be noticed that it takes the proposed OAERA algorithm an average run time of 500 iterations to realize an optimal solution, as the iteration number is observed to enhance the system attainable sum-throughput of the two systems. As a result, it is reasonable to utilize 500 iterations for averaging the performance of the system. Thus, the simulated results are obtained based on an average of 500 iterations using MATLAB. The running time for solving the optimization problem of timing allocation schedules for the harvesting of energy and transmission of information in a joint manner using the OAERA algorithm is linear in sensors A and B, has a lower computational time complexity for larger sensor nodes A and B, and takes about 0.060s for one run time compared to the exhaustive method in [204] that takes about 1s for one run time because of its exponential time complexity which makes it have a higher computational time complexity. The computer system used for running the simulations is AMD E1-1200 processor operating at 1.40 GHz and with 4 GB RAM specifications.

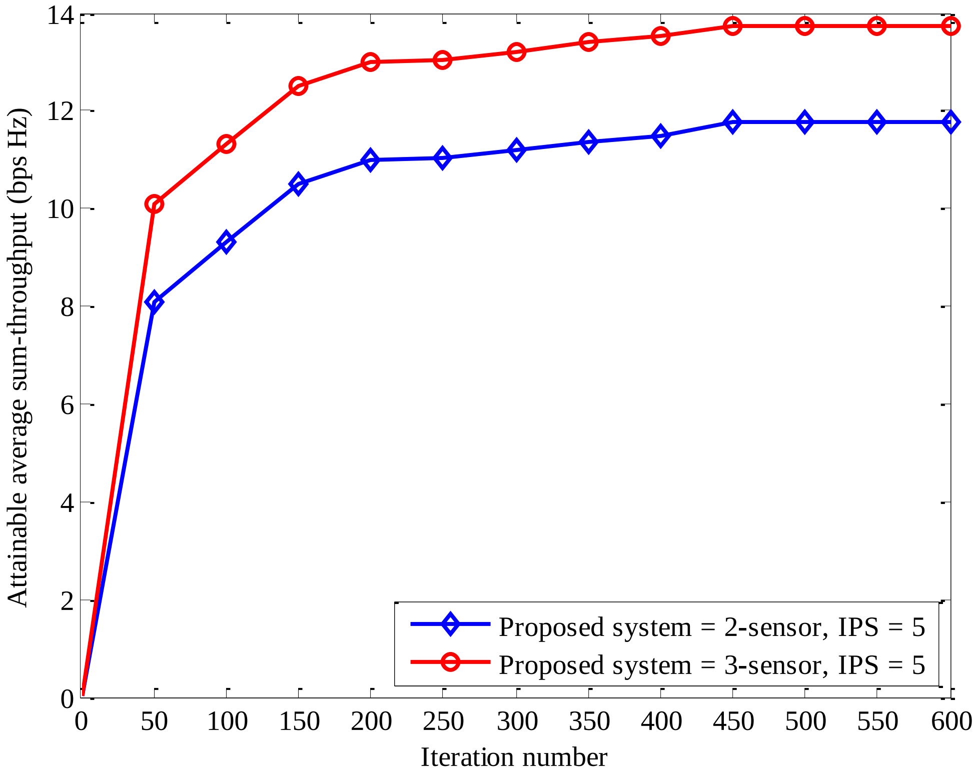

Figure 4.4. Attainable average sum-throughput of the system versus iteration number. The blue lines indicate a 2-sensor system, while the red lines indicate a 3-sensor system.

4.8.2 Path-loss exponent impact on the system attainable throughput

In the course of this experiment, the number of network sensor nodes is fixed and the channel path-loss exponent is varied to investigate the impact of path-loss exponent. The experiment is repeated for systems configured with 2, 3, and 4 sensors. Each of the systems is powered by 5 IPS. From the results in Figure 4.5, it is noticeable that there is a decrease in the system average attainable sum-throughput as the value of path-loss exponent increases. The reduction experienced in the system attainable throughput due to rise in path-loss exponent is valid in the 2-sensor, 3-sensor, and 4-sensor systems. Another observation is that, a system with 4-sensor had a higher average attainable sum-throughput compared to the systems with

2-sensor and 3-sensor. Therefore, it is confirmed that the system performs better when it is configured with a lower path-loss exponent value.

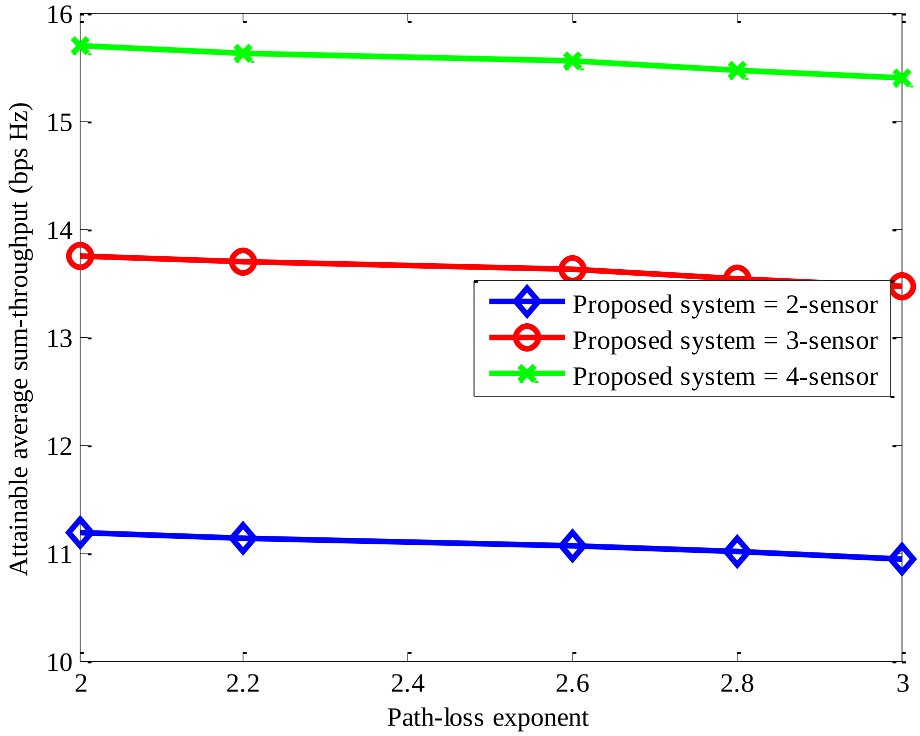

Figure 4.5. Attainable average sum-throughput versus path-loss exponent. The blue lines indicate a 2-sensor system, the red lines represent a 3-sensor system, while the green lines indicate a 4-sensor system.

4.8.3 Performance comparison of systems with different configurations

In this section, simulation investigations were carried out on the new WPSN application, and also on an existing WPSN application in [204]. The network sensor nodes are fixed, while the number of IPSes changes in the course of the experiment to investigate the impact of the number of IPSes on the overall attainable throughput rates and fairness index. Based on the simulation experiments, the proposed WPSN system was compared with the existing system in the context of the attainable average sum-throughput, and fairness. As in [204], two different system configurations were considered. One of the systems was configured with 2-sensor, while the other was configured with 3-sensor. The two systems are powered by 5 IPS. For the comparison of the proposed system and the existing system, the same simulation software is run, while the algorithm proposed is activated for the WPSN system of this work, and deactivated for the existing WPSN system. Consequently, the proposed WPSN system and the existing WPSN system are compared based on the attainable average sum-throughput and Jain's fairness as shown in Figures 4.6 and 4.7.

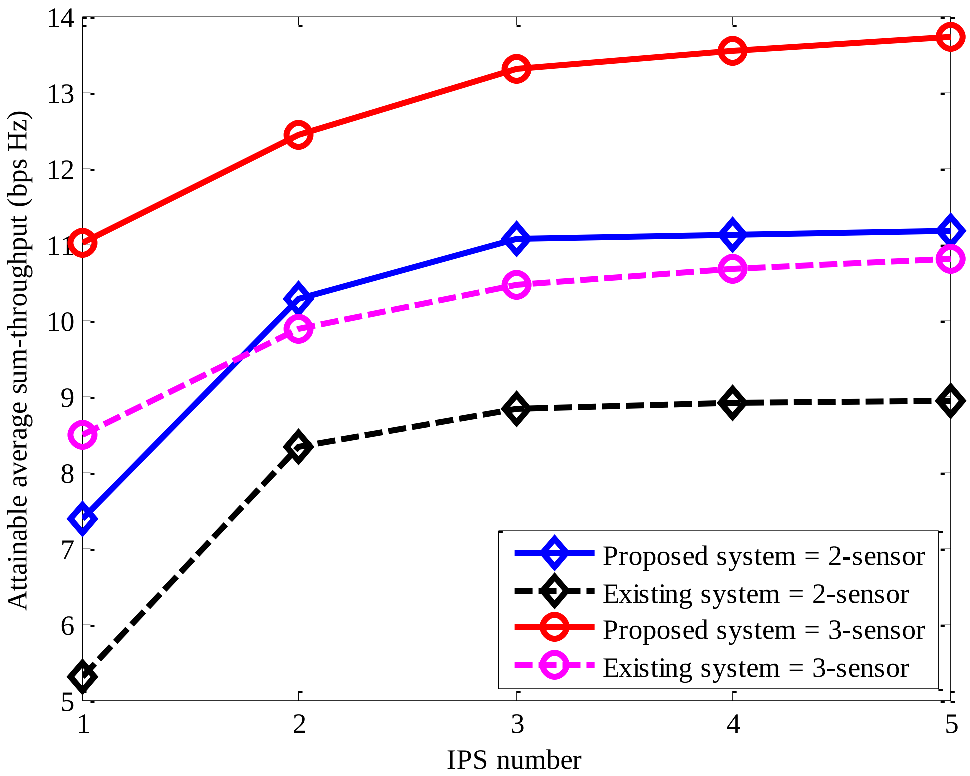

Figure 4.6. Attainable average sum-throughput versus number of IPS. The blue lines indicate a 2-sensor system, while the red lines indicate a 3-sensor system. The solid lines represent the proposed, while the dashed lines represent the existing system [204].

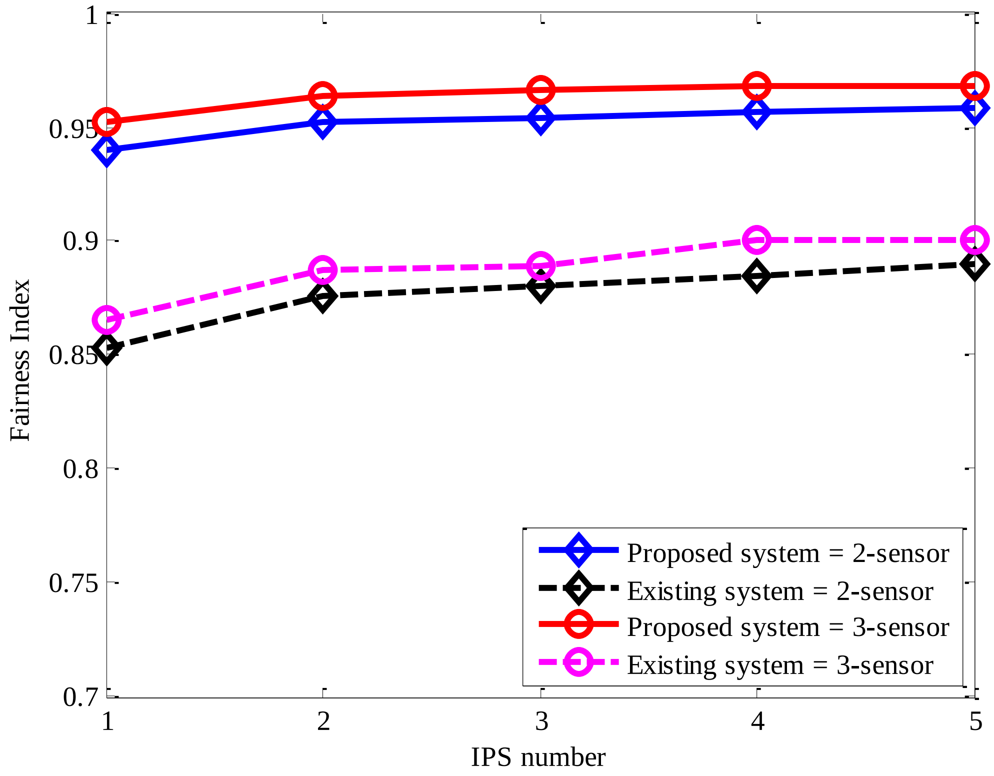

Figure 4.7. System fairness against IPS number. The blue lines indicate a 2-sensor system, while the red lines indicate a 3-sensor system. The solid lines represent the proposed, while the dashed lines represent the existing systems [204].

From Figure 4.6, it is noticeable that the proposed WPSN system outperforms the existing WPSN system, as it achieves an enhanced average sum-throughput. The improvement in the attainable sum-through results is as a result of the newly proposed algorithm. The new optimization algorithm efficiently allocates optimal time to DL-EH and UL-IT. In addition, through the results in Figure 4.6, it is easy and straightforward to infer that a 2-sensor system that is operated based on the proposed algorithm performs comparably to a 3-sensor system that is operated based on the existing algorithm. Moreover, the ratio of fairness in resource allocation between the sensor nodes in the network is investigated by employing the Jain's equation. As a consequence, from Figure 4.7, it is observed that the proposed WPSN system achieved enhanced fairness rates when compared to the existing 2-sensor system and 3-sensor system. This indicates an interesting improvement in fairness in the allocation of resources in the system, thus, addressing the inherent doubly-near-far issue in WPSN systems. From the results, it can be concluded that the proposed optimization algorithm optimizes the system sum-throughput by 26.46 % and 27.18 % for 2-sensor and 3-sensor, respectively, in comparison to the existing system. Similarly, the ratio of fairness of the proposed system configured with 2-sensor and 3-sensor, indicate improvements of 8.6 % and 8.5 %, respectively, compared to the existing system.

4.8.4 Comparison based on unequal network distances to the BS

The effect of unequal network distance to the BS between two classes of network is investigated in this section to emphasize the contributions of the newly proposed algorithm. The network distances to the BS are kept constant, while the number of IPSes is varied. To achieve this, we consider the deployment of Class A to the BS at 5.5 m, while Class B is 6.5 m from the BS. The two classes of network contain 3 sensors, powered by a number of intended 3W IPS sources, which is varied in different simulation runs. As illustrated in Figure 4.8, the results obtained are compared to the existing system with the same configuration, and it is apparent that a substantial increase of 25.68 % and 26.67 % in transmission throughput rate is attainable with the proposed system for Class A and Class B, particularly when the available energy is constrained by a small number of IPSes. Furthermore, Class A in the proposed system, which has a smaller distance to the BS, must spend lower energy on information transmission to the BS in the UL, and consequently, the network achieved a significant improvement in the attainable average sum-throughput compared to Class B.

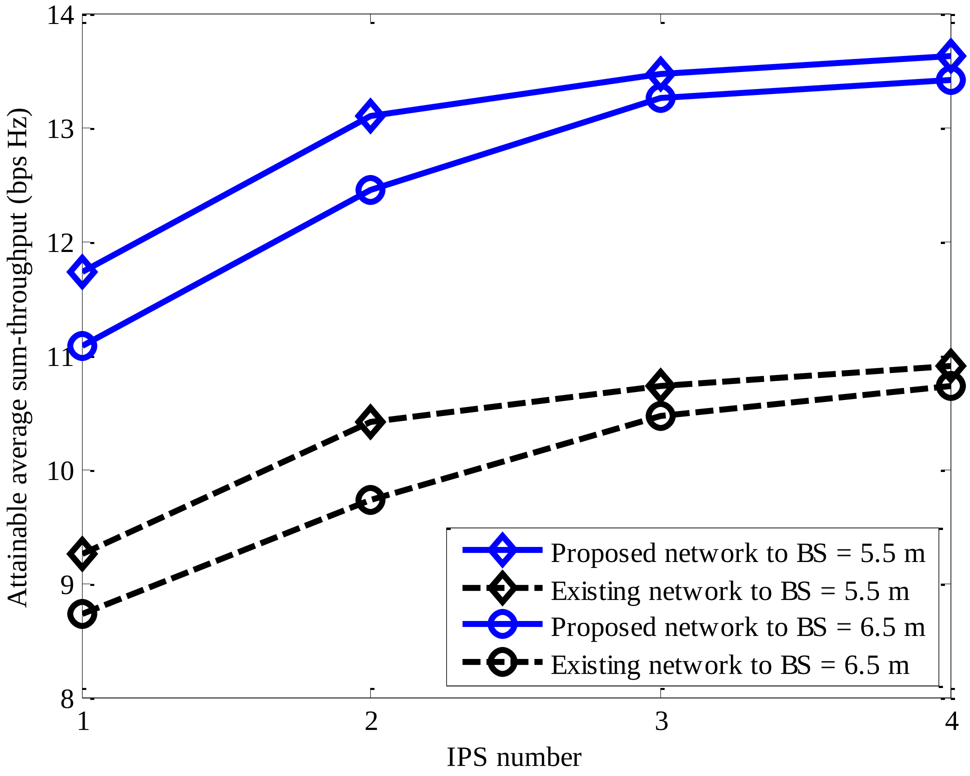

Figure 4.8. Attainable average sum-throughput based on unequal network distance. The solid blue lines indicate the proposed systems, while the dashed black lines indicate the existing systems [204].

4.8.5 Transmission power impact on the attainable throughput of the system

This section investigates the influence of transmission power on the attainable throughput rate of a system with 3-sensor, powered by a variable number of IPSes. To achieve this, the transmission power of the IPS is varied from 100 mW, 500 mW, 1000 mW to 3000 mW. As depicted in Figure 4.9, a great surge in the performance of the system is noticed as the IPS transmission power increases. Based on this observation, it can be corroborated that the IPS plays a crucial role in the attainable system sum-throughput rate in the context of transmission power value.

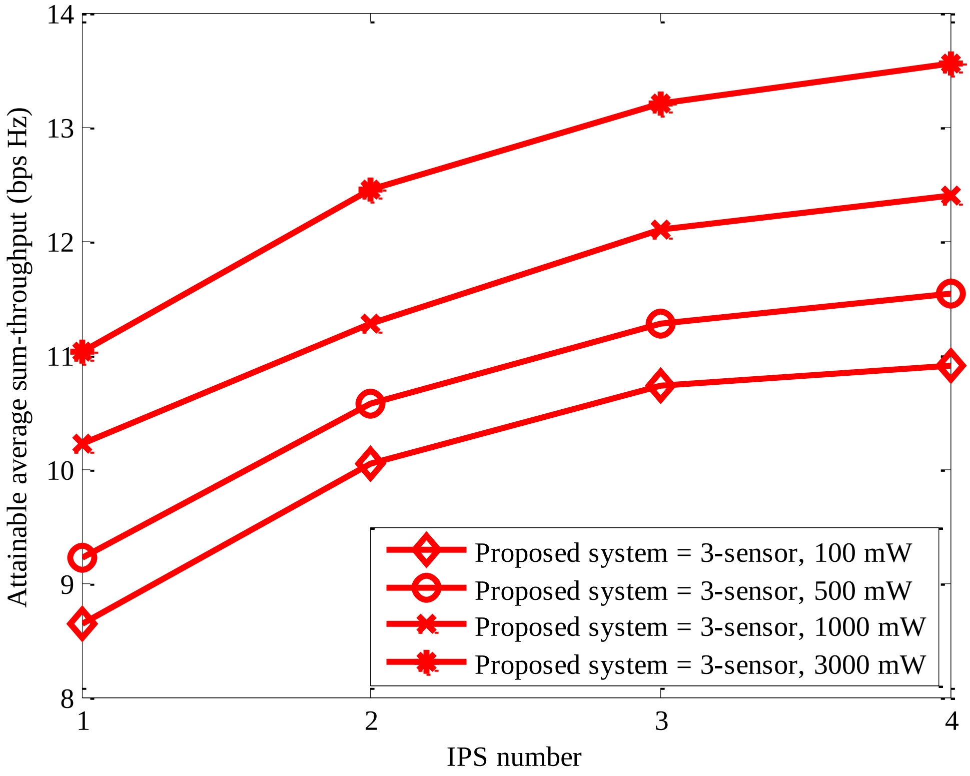

Figure 4.9. Attainable average sum-throughput against transmission power. The solid red lines indicate the proposed 3-sensor systems.

Similarly, with a larger number of IPS, the attainable overall throughput of the system performance gets better as more resources are being efficiently allocated to the network sensors in an optimal fashion. Furthermore, when the system is operated with 100 mW transmission power, which is quite low, the system performance is satisfactory. This is an interesting observation that depicts the proposed system's capability to efficiently utilize energy resources, with reliable network communication.

4.8.6 Comparison based on equal network distances to the BS

The effect of equal network distance to the BS between Class A and Class B networks is investigated in this section. As a result, the distances of the network classes are fixed, while the number of IPSes is varied in the course of the experiment. Class A and Class B were considered at an equal distance of 7.5 m to the BS. Each class contains 2 sensors and they are powered by a variable number of 3W IPS sources. The same investigation was carried out for 3 sensors. As illustrated in Figure 4.10, it is noticeable that Class A network only has a slight enhanced attainable sum-throughput compared to Class B network for 2 sensors, regardless of the unequal distances among the randomly placed Class B sensors, while the attainable throughput rate for 3 sensors was almost similar for classes A and B networks. As a consequence, it is apparent that the proposed optimization algorithm is able to efficiently handle resource allocation among the two classes of network in a fair manner by providing different optimal timing to Class B sensors based on their calculated distances to the available energy resources, as well as equal optimal timing to the sensor nodes in Class A.

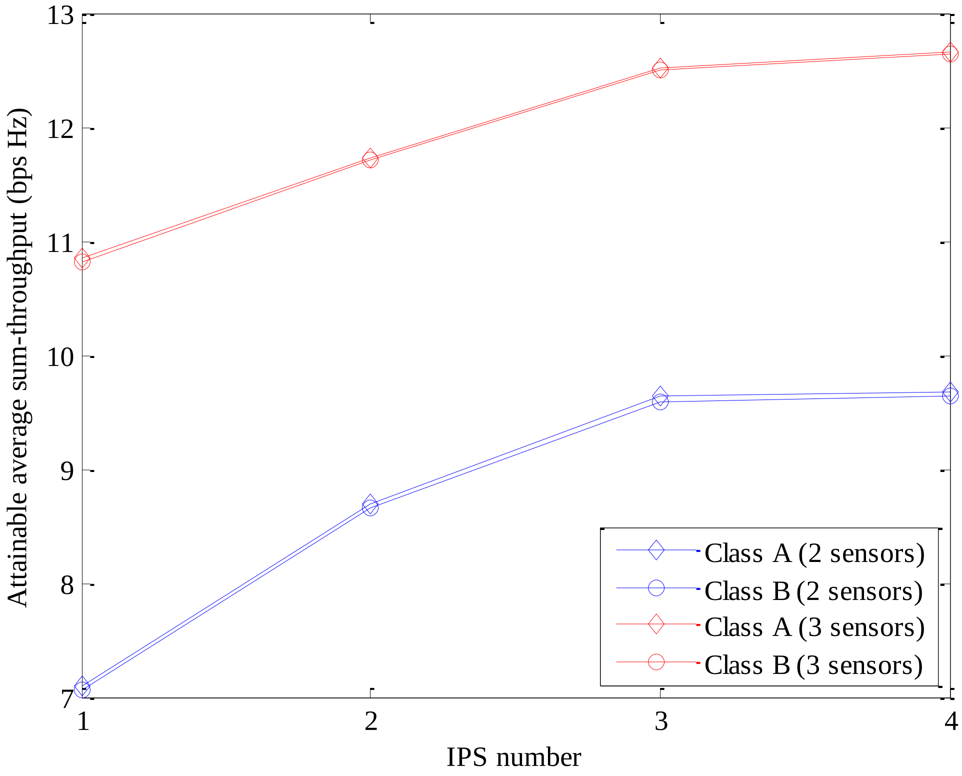

Figure 4.10. Attainable average sum-throughput based on equal network distance. The solid blue lines indicate the 2-sensor systems, while the red lines indicate the 3-sensor systems.

4.8.7 System performance based on fraction of energy consumed on information transmission

This section investigates the performance of the system, using a 3-sensor example, by varying the fraction of average power of transmission of the sensor nodes. Consequently, the number of both the network sensor nodes and the IPSes are fixed, as the average transmission power is varied. The system model is developed such that energy consumption for other networking processing has been optimized; therefore, it is possible to increase the amount of energy resources for information transmission. This is the basis for varying the fraction of average power of transmission.

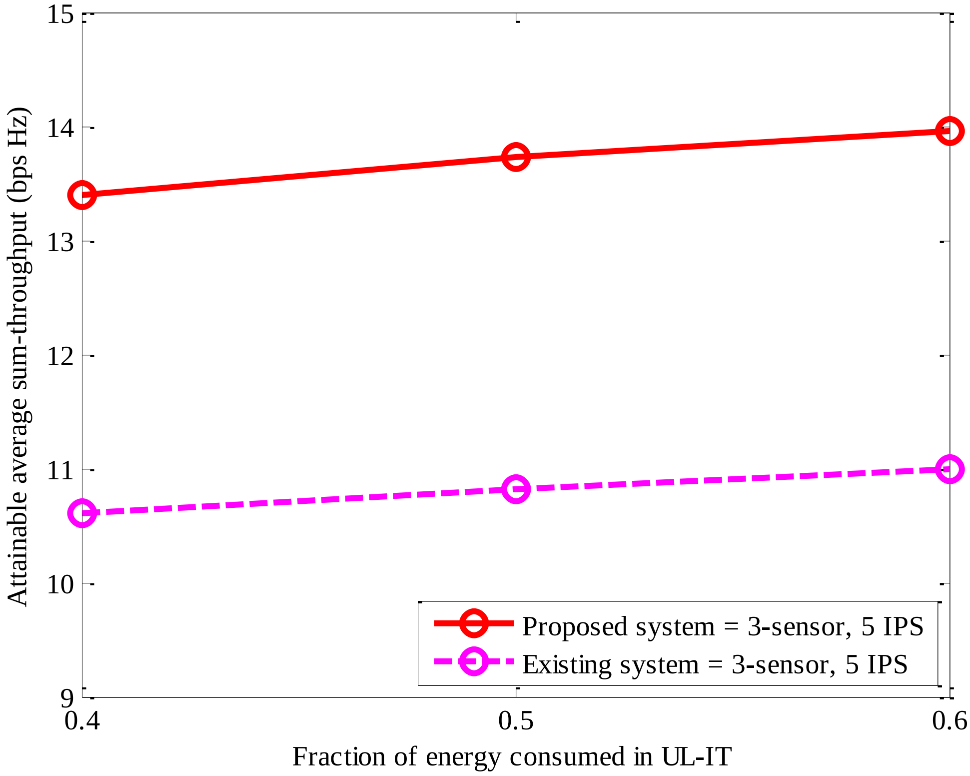

Figure 4.11. Attainable average sum-throughput against fraction of energy consumed on information transmission. The solid red lines indicate the proposed system, while the dashed magenta lines indicate the existing system [204].

From Figure 4.11, it is noticeable that the system throughput rate increases as the information transmission power of the sensor nodes in the network increases, as could be expected. The reason for this is that the sensor nodes can now spend higher energy on information transmission during the UL period, which in turn improved the system overall throughput. In addition, the results obtained in Figure 4.11 are compared to the existing system with the same configuration and it can be inferred that there is a significant improvement in the throughput rate of the proposed system. This is an indication that the proposed system is more energy-efficient in terms of energy consumption.

4.8.8 Comparison of system performance under different number of nodes in the network classes

In this section, the impact of different number of nodes in the network classes on the system performance is studied. To realize this, the number of nodes in Class A and Class B were unequal and constant, while number of IPSes was varied, in the course of simulation. Both classes A and B have an equal distance of 7.5 m to the BS. Comparison experiments were carried out on Class A containing 2 sensors and Class B containing 3 sensors; Class A containing 3 sensors and Class B containing 4 sensors, and Class A containing 2 sensors and Class B containing 4 sensors. Each experiment was powered by a variable number of 3 W IPS sources. From Figure 4.12, it is noticeable that in all three the experiments, Class B achieved a significant attainable throughput rate compared to Class A. The variation in the attainable throughput rates between Class A and Class B in the system is due to the number of sensor nodes contained in each network as the class with a higher number of nodes achieves a higher throughput rate compared to a class with a lesser number of nodes.

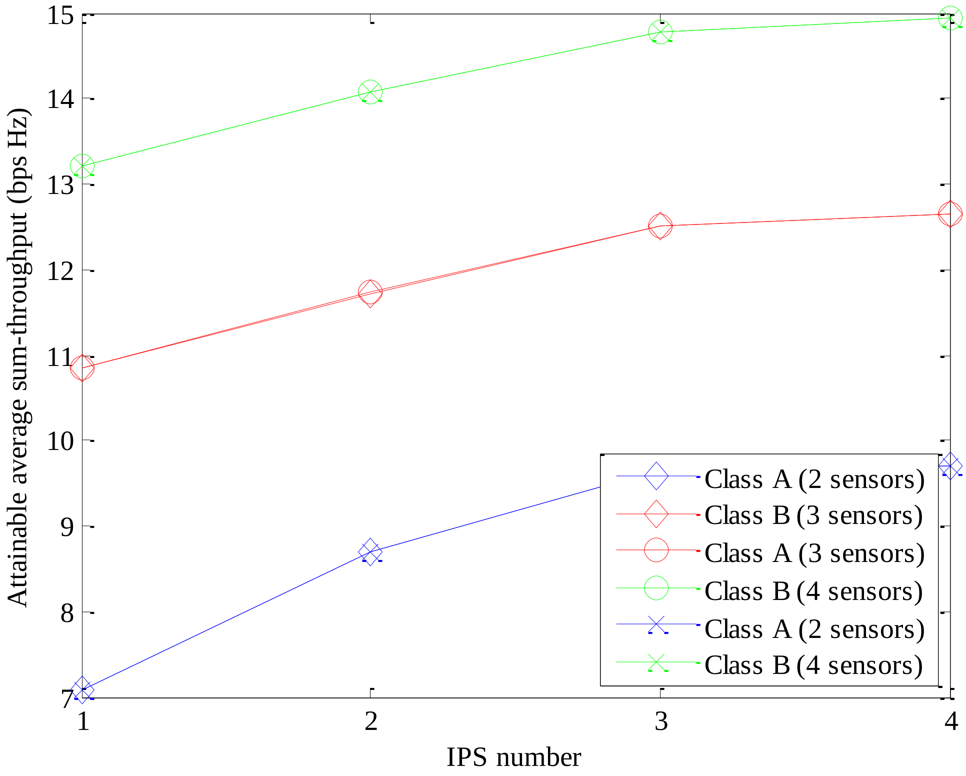

Figure 4.12. Attainable sum-throughput based on different number of nodes in the network classes. The solid blue lines indicate the 2-sensor systems, the solid red lines indicate the 3-sensor systems, while the solid green lines indicate the 4-sensor systems.

4.9 CHAPTER SUMMARY

This chapter has proposed a new approach to energy harvesting and data transmission optimization in a heterogeneous multi-class and multiple resource wireless transmission system that focuses on monitoring water and its quality. To achieve this, an optimal optimization algorithm that optimizes the energy and information timing schedules in a joint manner is proposed, and the proposed algorithm is validated in terms of path-loss exponent impact, performance comparison of systems, convergence based on iteration, comparison based on unequal network distances to the BS, transmission power impact on the attainable throughput and on the fraction of energy consumed on information transmissions, and influence of different number of nodes in the network classes. To reduce the system's energy consumption and to also enhance the system overall throughput rate, a sum-throughput optimization technique is employed. The proposed system has revealed advantageous results in the context of fairness and sum-throughput by efficiently allocating resources to the deployed sensor nodes based on a determined strategy for one class, and a random strategy for the other. The new WPSN system was compared with an existing system in [36] based on transmission throughput rate and fairness. The transmission throughput rate and fairness results of a system with 2-sensor employing the proposed algorithm performs comparably to a system with 3-sensor employing an existing algorithm proposed in [36], with all other network parameters the same. In addition, the proposed optimization algorithm, achieved a profitable transmission throughput rate regardless of the varying distances to the BS among the sensor nodes in Class B of the proposed WPSN, when compared to a system with the same configuration, but without the proposed optimization algorithm. Moreover, for an IPS power as low as 100 mW, the proposed system reveals an acceptable performance, which indicates it capability to efficiently utilize energy resources with reliable network communications. Furthermore, it is important to underline that the simulated systems are robust and optimal against failure due to the efficiency of the proposed solutions and the way the systems are carefully planned. The systems are flexible in nature, and so they can be re-adapted easily to a new environment because of the simplicity of the proposed optimization algorithms that have benefited the systems to make them slightly fragile in the modulations of environment.

For emphasis purposes, this chapter has catered for different energy efficient deployment strategies, network heterogeneity, efficient utilization of network resources (such as energy and time-slot) and an efficient communication protocol powered by a new TDMA scheme to optimize the use of the network resources and as well to improve the data communication performance of the system and efficiency. The next Chapter 5 focuses on improving the energy utilization, throughput and fairness performances of a WQM system that employs a random deployment strategy.

CHAPTER 5 MAXIMIZING THE THROUGHPUT AND FAIRNESS OF A WATER QUALITY MONITORING WIRELESS SENSOR NETWORK SYSTEM

5.1 CHAPTER OVERVIEW

In this chapter, a holistic solution for maximizing energy harvesting fairness and information throughput in a multi-network wireless sensor network system devoted to WQM applications, is developed. The overview of each section in this chapter is provided as follows. In Section 5.2, the background of the harmful impacts of water contaminations on the public health as well as the long-standing problems of the wireless sensor network systems intended for WQM purposes are discussed. Also, in this section, a sustainable energy solution for powering wireless sensor network systems deployed for WQM including a wireless information and power transfer (WIPT) concept are introduced. In Section 5.3, the review of the related literature is presented. Also, in Section 5.3, a new multi-group, multiple-source (MGMS) WIPT system for WQM is proposed, and the crucial contributions of the chapter are as well highlighted in this section. In Section 5.4, a system model for the new WIPT system is designed including the mathematical models for the proposed system. In Section 5.5, a maximization problem is formulated to jointly optimize the energy harvesting time and the information transmission rates allocation of sensor nodes to solve a doubly near-far problem, and to as well improve the energy efficiency of the system. In Section 5.6, a new energy efficient optimization algorithm for energy harvesting timing and information transmission rate allocation is designed, and Section 5.7 presents the simulation results. The chapter summary is presented in Section 5.8.

5.2 BACKGROUND

Recently, there have been efforts by researchers to develop novel sensing systems to monitor WQ parameters that include pH values and bacteria (often E. coli is used as indicator organism), in a timely manner, to complement the traditional systems employed in combating water pollution [210], [214], [230]. Annually, an estimate of about 250 million water-borne related diseases cases is reported around the globe, claiming about 5 to 10 million lives [62]. This is due to the increase in the influx of environmental and water pollutants such as organic and inorganic contaminants, through anthropogenic activities and natural processes [3], [215]. Consequently, water ingested from these processes is harmful to public health due to the presence of micro-organisms and metal ions such as mercury (Hg) and lead (Pb). Moreover, the metal ions are also environmental contaminants that indirectly create health issues such as cancer, organ damage, acute hepatic and renal failure, epigastric pain, and diarrhoea [4], [5], as well as other environmental concerns due to their high toxic characteristics [7], [8]. These issues have necessitated the need for effective WQM systems, frequently based on wireless sensor networks.

Currently, wireless sensor network systems are confronted by an energy scarcity problem [29]. This problem has been a long issue in wireless sensor networks due to the limited energy budget of battery-powered sensor nodes contained in wireless sensor network applications [115]. To achieve the objective of timely monitoring of WQ parameters without any interruption in energy supply, energy harvesting [231] is a promising approach that has been explored and exploited to replace battery power. Examples of energy harvesting techniques include RF energy harvesting [90], solar energy harvesting [71], and wind energy harvesting [91].

Among these techniques, energy harvesting from dedicated RF sources is controllable, and suitable to continuously monitor water distribution networks [99]. Furthermore, RF energy harvesting is useful over larger areas, since it is characterized by far-field energy radiation [99]. These benefits make the wireless RF power transfer energy harvesting technique more attractive choice for WQM applications in an enclosed environment. Currently, there are commercial dedicated RF power solutions, for example, a Powercaster transmitter [220], which is suitable for any location. Variants of Powercaster transmitters are RF power source TX91501, and battery-powered wireless transmitters [221]. These transmitters can be used to reliably send RF energy wirelessly to sensor nodes up to 24 m away by using the unlicensed industrial, scientific and medical (ISM) frequency bands [222]. Also, Powercast P2110 is a suitable RF energy harvester for Powercaster transmitters.

RF energy harvesting based on wireless information and power transfer (WIPT) system has emerged as an interesting technique to transfer energy from dedicated RF sources to a large number of sensor nodes in a network to achieve a stable supply of energy without any interruption in communication that may result due to energy depletion [99], [120]. This method is employed to harvest RF energy from dedicated RF sources, compared to the traditional energy harvesting method used to harness energy form ambient energy sources that include ambient RF. WIPT method is envisioned to provide a lasting solution to the problem of energy scarcity in the future wireless sensor network and Internet of Things (IoT) systems [120]. To address the long standing energy problems that have constituted limiting barriers to the productivity of wireless sensor network for WQM, WIPT method is employed in this chapter to achieve a more reliable wireless sensor network system with stable energy supply, efficient throughput for communicating WQ data and a sustainable quality-of-service (QoS) [120]. To achieve this, a new multi-group, multi-source WIPT system is investigated in this chapter. It is important to underline that wireless sensor network systems that employ WIPT method typically suffer from an unfairness issue which is basically referred to as a doubly near-far problem. The problem is a major limiting constraint of WIPT method and is technically responsible for inefficient energy resource utilization by the WQ sensors in a network. Considering the potential benefits of the WIPT method to wireless sensor networks in WQM, it is therefore a worthwhile investment to address the unfairness issue in WIPT method in a way to find solutions to the optimal utilization of the network resources so as to improve the productivity of wireless sensor network solutions in WQM applications.

5.3 RELATED LITERATURE

Most of the recent works on the development of wireless sensor network systems based on WIPT techniques focus on a single dedicated RF energy source. For example, in [128], the authors considered the investigation of a dedicated RF source to transfer energy to the sensor nodes. The optimization of the energy harvesting time and the information transmission time, were considered to address the effect of unfairness on information transmission rates. In [223], a WIPT system powered by a single dedicated RF source was considered to investigate the trade-off in communication channels throughput. In [202], a wireless sensor network powered by a dedicated RF energy source, and using complex self-recharging sensor nodes, was investigated. In [203], a wireless body area network WIPT system powered by a dedicated RF source was investigated. The authors also proposed two different protocols to optimize the information transmission rates of each sensor node to the access point, by balancing the energy harvesting time and the information transmission time of their WIPT system.

In [204], the use of multiple dedicated RF sources is proposed. The joint optimization of the energy harvesting time and the information transmission time of a WIPT system for an on-body wireless sensor network application was investigated in a dynamic environment. The authors also considered the calculation of the proportion of the energy harvesting time-period allocated to each dedicated RF energy source to transfer energy to a sensor node, which is dependent on the movement of the object carrying the sensor nodes.

A new type of WIPT system is considered in this chapter. To address the doubly near-far problem, a multi-group network was proposed. In the proposed network, the sensor nodes are randomly deployed in a static environment. Different from [204], we introduce a new parameter to allocate different energy harvesting time to the sensor nodes based on their distance from the dedicated RF sources. Based on the new energy harvesting time period parameter, T_{EH}, an optimal shorter time is allocated to the group of sensor nodes that are close to the dedicated RF sources, while an optimal larger time is allocated to the group of sensor nodes that are far from the dedicated RF sources in the DL. Moreover, to achieve similar information transmission rates among the sensor nodes in the UL, the sensor nodes that are far from the sink node are allocated a longer information transmission time in order for them to have enough time to transfer their independent information.

In WIPT systems, there are four basic types of RF receiver architectures employed for energy harvesting and information transmission. They include power splitting RF receiver, time-switching RF receiver, separated RF receiver, and integrated RF receiver architectures [99]. Among these RF receiver architectures, time-switching RF receiver architecture is suitable for efficient RF energy harvesting [99], [204], compact in size [204], and ease of integration into sensor nodes without increasing the form factor of sensor nodes [229]. The existing solutions that are employed in the time-switching RF receiver architecture, are confronted by problems of unfairness in both energy harvesting, and information transmission rates, unless efficient schemes are being put in place to effectively manage the time switching of the RF receiver antenna between the energy harvesting circuitry, and the information decoding circuitry [225]. Another issue is the problem of interference in energy transmission when multiple dedicated RF sources are deployed [27], [201]. These issues are addressed in this chapter by considering a multi-group, multiple-source WIPT system for WQM. Moreover, this chapter is aimed at ensuring that all the sensor nodes that make up the proposed multi-group, multi-source WIPT system, harvest enough energy required for their independent information transmission with the expected QoS at all times, while addressing the doubly near-far problem. The principal contributions of this chapter are described as follows:

- To address efficient energy harvesting and information transmission timing in the proposed WIPT system, a new TDMA model is formulated.

- The formulated TDMA model is used to jointly optimize the energy harvesting time in the DL channels, and the information transmission time in the UL channels of the sensor nodes, in order to maximize the sum-throughput rate of the proposed WIPT system.

- The calculation of optimal energy harvesting time allocation in a random deployment scenario of sensor nodes for efficient energy harvesting timing and increased information transmission rates.

- Development of a dedicated RF source allocation and information transmission algorithm to improve fairness in energy harvesting and information transmission rates among the sensor nodes.

This chapter is divided into the following sections: Section 5.4 presents the architecture of the system and the formulated TDMA model for the proposed multi-group, multi-source WIPT system. Section 5.5 presents the joint optimization of the energy harvesting and information transmission rate problem and Section 5.6 described an efficient algorithm for multiple dedicated RF sources allocation and information transmission timing. The system sum-throughput and fairness results are presented in Section 5.7 to validate the sum-throughput optimization problem. Section 5.8 presents a concluding remark.

5.4 SYSTEM MODEL

In the system model, we consider an RF powered multi-group, multi-source WIPT system that contains two groups of network. Let $\{n_1, n_2, .., N\}$ denote the set of WQ sensor nodes n in Network 1, $\{m_1, m_2, .., M\}$ denote the set of WQ sensor nodes m in Network 2. Also, a set of dedicated RF sources represented by $\{g_1, g_2, .., G\}$ are deployed in the system at some positions. To provide sufficient energy for powering the WQ sensor nodes, more dedicated RF sources are deployed. The body of the water to monitor is channeled into an improvised water monitoring section in an enclosed environment that provides a suitable platform for the random attachment of the WQ sensors, and a continuous flow of water. The WQ sensor nodes are used to monitor parameters such as E. coli and pH. A multi-network technique is employed to ensure the closeness of the sensor nodes to the dedicated RF sources as described in Figure 5.1. Among the g's, only g_1 can both transmit energy, and receive independent WQ information in the UL, also, it provides communication gateway to the Internet through which WQ measured information are sent to WQM centers. The dedicated RF sources are all connected to a controller, and their transmissions are strictly controlled by a new proposed TDMA model, to prevent destructive interference to the transmitted wireless energy. Based on the proposed TDMA model, only one dedicated RF energy source can transmit energy at a time, while only one sensor node can harvest energy at a time, as well.

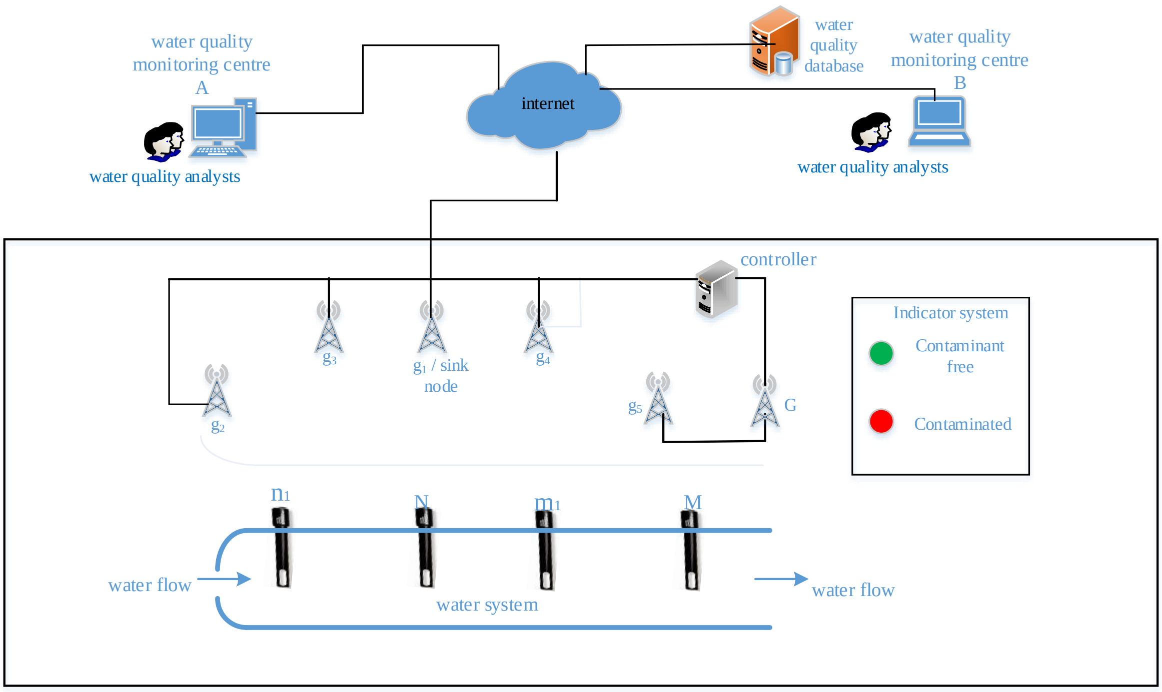

Figure 5.1. System model for WQM in a water processing station.

Due to the random deployment of the sensor nodes, there exist unequal distances among the sensor nodes to the dedicated RF sources. As a consequence, the energy harvested by the sensor nodes is affected by the wireless channel conditions of the system, since some sensor nodes are close to the dedicated RF sources, while some are far. To address this doubly near-far problem, an optimal larger time is calculated and allocated to far sensor nodes for sufficient energy harvesting, while an optimal shorter time is calculated and allocated to the closer or nearby sensor nodes to harvest energy. Each sensor node n and m in networks 1 and 2, is equipped with an omnidirectional antenna. A harvest-then-transmit approach is employed based on the proposed TDMA protocol in Figure 5.2, such that either the RF energy harvester, or the information receiver, is connected to the antenna at a given time.

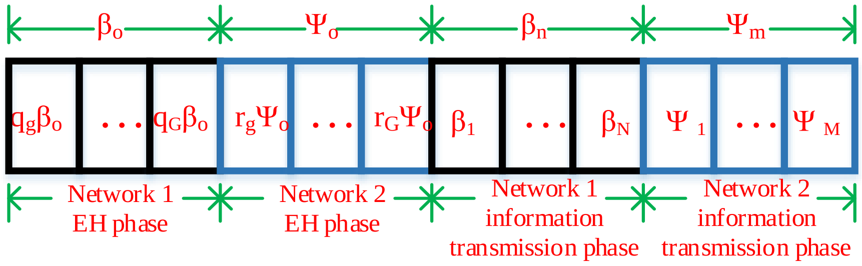

Figure 5.2. Proposed energy harvesting and information transmission TDMA scheme

The wireless sensor network application environment is assumed to be static, and the channel from a dedicated RF source g to sensor nodes n and m is modelled as a quasi-static block fading model, and the channel gains are obtained as a feedback from the sensor nodes. The channels from sensor nodes n and m to the sink node g_1 in the UL, and the reversed DL channel from a dedicated RF source g in the DL, are represented with complex variables $\tilde{a}_{g,n}$ and $\tilde{b}_{g,n}$, $\tilde{f}_{g,m}$ and $\tilde{h}_{g,n}$ for Network 1 and Network 2, respectively, while the channel power gains are $a_{g,n} = |\tilde{a}_{g,n}|^2$, $b_{g,n} = |\tilde{b}_{g,n}|^2$, $f_{g,m} = |\tilde{f}_{g,m}|^2$, and $h_{g,m} = |\tilde{h}_{g,m}|^2$ for Network 1 and Network 2, respectively. Also, the channel state information (CSI) is assumed to be known to the dedicated RF sources, thus, energy is adaptively transferred based on the channel conditions. The dedicated RF sources use the CSI to access sensor node n and m, and transmit an optimal energy.

The proposed multi-group, multi-source WIPT system is described further as follows:

Network 1:

In each given β_0, according to the TDMA model presented in Figure 5.2, the calculated energy harvesting time with a length of $0 \leq q_1\beta_0 \leq 1$ is assigned to a dedicated RF source g to transfer energy to sensor node n in the DL, while the time allocated to sensor node n to transmit its information in the UL to the sink node g_1 over channel $a_{1,n}$, is represented with time period β_n, $n = 1, 2, \ldots, N$, with a length of $0 \leq \beta_n \leq 1$. Therefore, the time allocated to a dedicated RF energy source g to transmit energy to sensor node n in Network 1 in the

DL, and the time allocated to sensor nodes *n* to transfer their independent information in the UL, is given by:

$$\sum_{g=1}^{G} q_g \beta_0 + \sum_{n=1}^{N} \beta_n \leq 1 \tag{5.1}$$

The power received by sensor node *n* from a dedicated RF energy source is given as:

$$x_{g,n} = \sqrt{b_{g,n}}\, x_{A,g} + z_n, n = 1,2, \dots, N \tag{5.2}$$

where $x_{g,n}$ and z_n represents the received signal and the background noise at sensor node *n* from a dedicated RF energy source g, respectively. $x_{A,g}$ denotes the arbitrary complex random signal of a dedicated RF source g that satisfies $E\left[\left|x_{A,g}\right|^2\right] = P_{A,g}$, where $P_{A,g}$ represents the transmit power of a dedicated RF energy source g. The notation $E|.|$ denotes an expectation operator, while $|.|$ represents the magnitude of an argument. The transmit power $P_{A,g}$ is assumed to be large enough, thus, the background noise at the receiver *n* is negligible. Therefore, the amount of energy sensor node *n* harvests in the DL in each time-slot from a dedicated RF energy source g is expressed as:

$$E_{g,n} = \eta_n P_{A,g}\, b_{g,n} q_g \beta_0, g = 1,2, \dots, G, n = 1,2,..,N \tag{5.3}$$

Moreover, the total energy that sensor node *n* receives from the dedicated RF sources g is given by:

$$E_n = \eta_n \sum_{g=1}^{G} P_{A,g}\, b_{g,n} q_g \beta_0, n = 1,2, \dots, N \tag{5.4}$$

where η_n is the energy harvesting efficiency of sensor node *n*, $0 \leq \eta_n \leq 1$, *n=1,2,...,N.* It is assumed for convenience that $\eta_1 = \cdots = \eta_N = \eta$.

After harvesting energy in the DL phase, a fixed fraction of the energy harvested based on Equation (5.4) is used by each sensor node n to transmit its independent information in the UL to the sink node g_1. The average transmit power of sensor node n for information transmission, is denoted by P_n and is given by:

$$P_n = \frac{\varsigma_n E_n}{\beta_n}, n = 1, \ldots, N \tag{5.5}$$

where ς_n denotes a fixed fraction of the energy harvested used by sensor node *n* to transmit its independent information in the UL to the sink node. For the purpose of simplicity, it is assumed that, $\varsigma_n = \cdots = \varsigma_N = \varsigma$, while the remaining portion of $1 - \varsigma$ is used for operating the sensor node *n* and its modules.

The received signal at the sink node g_1 from sensor node *n* in each UL time-slot is given by:

$$x_{g_1,n} = \sqrt{a_{1,n}}\, x_n + z_{g_1}, n = 1, \ldots, N \tag{5.6}$$

where $x_{g_1,n}$ and z_{g_1} are the received signal and the background noise at the sink node g_1 respectively, x_n denotes a random signal due to sensor node *n* that satisfies $\mathrm{E}[|x_n|^2] = P_n$. The channel capacity of the UL information transfer from sensor node *n* to the sink node g_1, is given according to Shannon's law of channel capacity as [208]:

$$C_n = \beta_n log_2\left(1 + \frac{P_n a_{1,n}}{\Gamma\sigma^2}\right) \tag{5.7}$$

where β_n denotes the information transmission time-slot (channel bandwidth) for sensor node *n*, P_n is the average transmit power of the sensor node *n*, Γ denotes the signal to noise ratio (SNR) gap of the sensor node with respect to the background noise of the receiver, σ^2 represents the thermal power noise due to the additive white Gaussian noise (AWGN). For sensor node n information transmission, the maximum achievable throughput in bits/second/Hz (bps/Hz) of sensor node *n*, denoted by R_n , cannot exceed the channel capacity, C_n, between the sensor node *n* and the sink node g_1. Therefore,

$$R_n \ \leq \beta_n log_2\left(1 + \frac{P_n a_{1,n}}{\Gamma\sigma^2}\right) \quad (5.8)$$

By substituting (5.5) and (5.4) into (5.8), the throughput rate can be derived in the form of

$$R_n \ (q, \beta) = \beta_n log_2\left(1 + \alpha_n \frac{\sum_{g=1}^{G} q_g \beta_0}{\beta_n}\right), n = 1, \ldots, N \quad (5.9)$$

where $q = [q_1, q_2, q_3, \ldots, q_G]$,$\beta = [\beta_0, \beta_1, \ldots, \beta_n]$, and α_n denotes the received SNR at the sink node g_1 as a result of the information transmitted by sensor node *n*, and is expressed as:

$$\alpha_n \ = \frac{\varsigma_n \eta_n a_{1,n} \sum_{g=1}^{G} \ P_{A,g}\, b_{g,n} q_g}{\Gamma\sigma^2} \ , n = 1, ., N \quad (5.10)$$

Subsequently, the sum-throughput of all sensor nodes *n* is given by:

$$R_{sum} \ (q, \beta) = \sum_{n=1}^{N} R_n \ (q, \beta), n = 1,2, . . , N \quad (5.11)$$

Network 2:

In each given Ψ_0, according to the TDMA model presented in Figure 5.2, the calculated energy harvesting time with a length of $0 \leq r_1\Psi_0 \leq 1$ is assigned to a dedicated RF energy source *g* to transfer energy to sensor node *m* in the DL, while the time allocated to sensor node *m* to transmit its information in the UL to the sink node g_1 over channel, $f_{1,m}$, is represented with Ψ_m, *m = 1, 2, …, M,* with a length of $0 \leq \Psi_m \ \leq 1$. Therefore, the time allocated to a dedicated RF source g to transmit energy to sensor node *m* in Network 2 in the DL, and the time allocated to all the sensor nodes *n* to transmit their independent information in the UL, is given by:

$$\sum_{g=1}^{G} r_g \Psi_0 + \sum_{m=1}^{M} \Psi_m \leq 1 \tag{5.12}$$

The power received from a dedicated RF source by sensor node *m* is given as:

$$x_{g,m} = \sqrt{h_{g,m}}\, x_{A,g} + z_m, m = 1, \dots, M \tag{5.13}$$

The amount of energy sensor node *m* harvests in the DL in each time-slot from a dedicated RF source g is expressed as:

$$E_{g,m} = \eta_m P_{A,g}\, h_{g,m} r_g \Psi_0, g = 1,2, \dots, G, m = 1,2, .., M \tag{5.14}$$

Therefore, the total energy sensor node *m* harvests from the dedicated RF sources g is given by:

$$E_m = \eta_m \sum_{g=1}^{G} P_{A,g}\, h_{g,m} r_g \Psi_0, \ m = 1,2, .., M \tag{5.15}$$

where η_m is the energy harvesting efficiency of sensor node *m*, $0 \leq \eta_m \leq 1$, *m=1,2,…,M.* Once again, it is assumed for convenience that $\eta_1 = \cdots = \eta_M = \eta$.

From (5.15), the average transmit power of sensor node *m* is P_m, and is given by:

$$P_m = \frac{\varsigma_m E_m}{\Psi_m}, m = 1,2, \dots, M \tag{5.16}$$

where ς_m denotes a fixed fraction of the energy harvested used by sensor node *m* to transmit its independent information in the UL to the sink node. For the purpose of simplicity, it is assumed that, $\varsigma_m = \cdots = \varsigma_M = \varsigma$, while the remaining portion of $1 - \varsigma$ helps to keep sensor node *n* running.

The received signal at the sink node g_1, from sensor node *m*, in each UL time-slot, is given by:

$$x_{g_1,m} = \sqrt{f_{1,m}}\, x_m + z_{g_1}, m = 1,2,.,M \quad (5.17)$$

According to Shannon's law of channel capacity, the channel capacity of the UL information transfer from sensor node *m* to the sink node g_1, is given as:

$$C_m = \Psi_m log_2 \left(1 + \frac{P_m f_{1,m}}{\Gamma\sigma^2}\right) \quad (5.18)$$

For sensor node *m* information transmission, the maximum achievable throughput rate in bps/Hz of sensor node *m*, denoted by R_m , cannot exceed the channel capacity, C_m , between the sensor node *m* and the sink node g_1, and therefore,

$$R_m\ (r, \Psi) = \Psi_m log_2 \left(1 + \gamma_m \frac{\sum_{g=1}^{G} r_g \Psi_0}{\Psi_m}\right), m = 1,2,,M \quad (5.19)$$

where $r = [r_1, r_2, r_3, \dots, r_G]$,$\Psi = [\Psi_0, \Psi_1, \dots, \Psi_m]$, γ_m denotes the received SNR at the sink node g_1 as a result of the information transmitted by sensor node *m*, and is expressed as:

$$\gamma_m = \frac{\varsigma_m \eta_m f_{1,m} \sum_{g=1}^{G} P_{A,g}\, h_{g,m} r_g}{\Gamma\sigma^2}, m = 1,..,M \quad (5.20)$$

Hence, the sum-throughput of all sensor nodes *m* is given by:

$$R_{sum}\ (r, \Psi) = \sum_{m=1}^{M} R_m\ (r, \Psi), m = 1,2,..,M \quad (5.21)$$

5.5 ACHIEVABLE THROUGHPUT MAXIMIZATION PROBLEM

The WIPT system achievable throughput is studied in this section by employing a sum-throughput maximization method to jointly optimize the energy harvesting time and the information transmission rates allocation of sensor nodes *n* and *m*. This will help to achieve an increased fairness in energy harvesting timing allocations, and increase in the information transmission rates of the sensor nodes, resulting in an improved system achievable throughput. The maximization problem of the achievable throughput of the system is formulated from (5.1) as (P6).

(P6):

$$\max_{q,\beta,r,\Psi} R_{sum}\ (q,\beta) + R_{sum}\ (r,\Psi) \tag{5.22}$$

subject to:

$$\sum_{g=1}^{G} q_g\, \beta_0 + \sum_{g=1}^{G} r_g\, \Psi_0 + \sum_{n=1}^{N} \beta_n + \sum_{m=1}^{M} \Psi_m \leq 1 \tag{5.22a}$$

$$q_g \geq 0, g = 1,2,..,G \tag{5.22b}$$

$$r_g \geq 0, g = 1,2,..,G \tag{5.22c}$$

$$\beta_n \geq 0, n = 1,2,..,N \tag{5.22d}$$

$$\Psi_m \geq 0, m = 1,2,..,M \tag{5.22e}$$

where (5.22) is the objective function, constraint (5.22a) represents the energy harvesting and information transmission time scheduling, while constraints (5.22b), (5.22c), (5.22d), and (5.22e) represent the non-negative constraints for the decision variables. The unknown variables in (P6) are q, r, β, Ψ. (P6) is a non-convex problem since (5.9) and (5.19) contain a *log* function. By a change of variable $q_g\beta_0$ to $\beta_{0,g}$, $r_g\Psi_0$ to $\Psi_{0,g}$, and obtaining the natural *log* of the *log* function in (5.9) and (5.19) respectively, the transformation of (P6) to a convex optimization problem (P7) is obtained. The proof for the transformed problem is described in Addendum C.1. (P7) can be solved by employing any convex optimization method [35]. Furthermore, to address energy harvesting unfairness among the sensor nodes due to the problem transformation, a new problem is formulated to ensure optimal values of q and r denoted as q^* and r^*. The optimal values of q^* and r^* are used in (P6) to ensure energy harvesting fairness among sensor nodes n and m. The energy harvesting unfairness minimization problem is formulated as (P8).

(P8):

$$\min_{q^*,r^*} E[(E_n - \bar{E}_n)^2 + (E_m - \bar{E}_m)^2] \tag{5.23}$$

subject to:

$$\sum_{g=1}^{G} q_g + \sum_{g=1}^{G} r_g = 1 \tag{5.23a}$$

$$q_g \geq 0, g = 1,2,..,G \tag{5.23b}$$

$$r_g \geq 0, g = 1,2,..,G \tag{5.23c}$$

where $\bar{E}_n$ and $\bar{E}_m$denotes the minimum energy harvested by sensor nodes n and m. $\bar{E}_n$ is calculated using:

$$E_n = E(E_n) = \frac{\sum_{n=1}^{N} E_n}{N} \tag{5.24}$$

$\bar{E}_m$is calculated using:

$$E_m = E(E_m) = \frac{\sum_{m=1}^{M} E_m}{M} \tag{5.25}$$

(P6) depends on variables q, r, β_0, Ψ_0, and these variables are yet unknown. To solve for an intermediate set of harvested energy E_n, *n = 1, 2,…, N* and E_m, *m = 1, 2, …, M*, non-zero arbitrary values can be assumed for β_0 and Ψ_0. Finding $q*$ and $r*$ is achieved as described in the proof for the energy harvesting unfairness minimization problem, given in Addendum C.2.

Furthermore, an algorithm for handling the allocation of multiple dedicated RF sources is proposed for energy harvesting efficiency and fair information transmission rate allocation. To determine the information transmission rate fairness between sensor nodes *n* and *m*, the concept of the Jain's fairness index is employed. According to [28], the Jain's fairness equation is

$$J = \frac{\left(\sum_{i=1}^{u} R_u\ (\delta)\right)^2}{u.\sum_{i=1}^{u}\left(R_u\ (\delta)\right)^2} \tag{5.26}$$

where $u = n + m$ denotes the complete network of sensor nodes *n* and *m*, while $\delta = \beta + \Psi$ denotes the combined time length for network 1 (sensor nodes *n)*, and network 2 (sensor nodes *m)*. Similarly, $R_u(\delta) = R_n(\beta)$+ $R_m(\Psi)$ denotes the summation of the sum-throughput of network 1 and network 2. Also, the worst case, and the best case, for sensor nodes *n* and *m,* is defined by

$$\frac{1}{U} \leq J_{FI} \leq 1 \tag{5.27}$$

$\frac{1}{U}$ denotes a minimum fairness rate, while the maximum fairness rate is 1.

5.6 PROPOSED ALGORITHM FOR OPTIMIZED ENERGY HARVESTING TIMING AND INFORMATION TRANSMISSION RATE ALLOCATION

In an attempt to provide fairness in energy harvesting timing among the sensor nodes in the WIPT system, and to also improve the information transmission rate of the sensor nodes, the energy harvesting and the information timing of the WIPT system are optimized in a joint manner. Based on the mathematical formulations of Section 5.5, Algorithm 4 is proposed to optimally allocate the dedicated RF sources to the sensor nodes at a calculated optimal time. In a similar vein, to ensure that each of the sensor nodes is provided a sufficient time to transmit its information in the UL, an optimal information transmission time is calculated and allocated. Algorithm 4 is implemented on the system controller to control the switching of the dedicated RF sources, including their optimal allocation to the sensor nodes in order to improve the WIPT system achievable throughput.

Algorithm 4. Efficient allocation of dedicated RF sources and information transmission timing

Require: $\{n_1, n_2, .., N\}, \{m_1, m_2, .., M\}$ > sensor nodes n and m ;

$\{g_1, g_2, .., G\}$> dedicated RF sources g

Ensure: $q_g^*, r_g^*,\ g = 1,2 \dots, G$ > optimal energy harvesting time

$\beta_n^*, \Psi_m^*, n = 1,2 \dots, N, m= 1,2 \dots, M$ > optimal information transfer time.

energy harvesting timing in the DL

1: for $g = 1{:}G$ do

2: set g to ON

3: for $n = 1{:}\ N$ do

4: calculate the distance of sensor node n in meters to the available g's

5: allocate energy time to sensor node n based on its distance in meters to the available g's for energy harvesting

6: end for

7: end for

8: for $g = 1{:}G$ do

9: set g to ON

10: for $n = 1{:}\ M$ do

11: calculate the distance of sensor node m in meters to the available g's

12: allocate energy time to sensor node m based on its distance in meters to the available g's for energy harvesting

13: end for

14: end for

Information transmission timing in the UL

15: set g_1 to ON

16: for $n = 1{:}\ N$ do

17: calculate the distance of sensor node n in meters to g_1

18: if n is close to g_1

19: allocate an optimal short time to n transmit its independent information

20: else

21: allocate an optimal larger time to n to transmit its independent information

22: end for

23: set g_1 to ON

for $m = 1{:}\ M$ do
  calculate the distance of sensor node m in meters to g_1
    if m is close to g_1
      allocate an optimal short time to m transmit its independent information
    else
      allocate an optimal larger time to m to transmit its independent information
  end for
end

5.7 SIMULATION RESULTS

In this chapter, through simulation experiments, Algorithm 4 as presented in Section 5.6, is shown to be computationally efficient through extensive evaluation in MATLAB environment. For the purpose of comparison, the same network parameters were assumed with [204]. The proposed WIPT system was configured using the simulation parameters in Table 5.1, while the algorithm was implemented on the proposed WIPT system. Two groups of network are deployed at 2 m apart in an environment of 20 m by 20 m. The two groups of network are considered at an equal distance of 7 m to the sink node. Network 1 contains randomly deployed sensor nodes *n*, while network 2 contains randomly deployed sensor nodes *m*. In each network, the WQ sensor nodes are deployed at a distance of 3 m from each other – as typical in WQM. As well, the distance between the sensor nodes can be varied. Also, the dedicated RF sources are considered at different strategic positions during optimization.

Table 5.1. Simulation parameters

Parameter	Value
Carrier Frequency	915MHz
Channel bandwidth	1 MHz
Noise power	-114 dBm
Transmission power of the dedicated RF sources	3000 mW
Energy harvesting efficiency	0.5
Fraction of energy used for information transmission	0.5
Pathloss exponent	2.0
Medium access control layer	IEEE 802.15.4
Signal-to-noise gap	1.5 dB

The simulated results for the proposed system are obtained using MATLAB and are provided based on the effect of the number of sensor nodes on the network performance, while the impact of pathloss exponent value on the system performance is also considered, and the influence of the transmit power on transmission rate is also investigated. The performance of the system is also comparatively verified as far as the number of dedicated RF sources in the system is concerned, as well as in terms of the Jain's fairness index. Lastly, the network performance improvement contributed by this work is substantiated with simulations with unequal distances between the two networks and the sink node. All results are obtained from an average of 500 simulation runs. The used computer system for running the simulations use an AMD E1-1200 processor that operates at 1.40 GHz and with 4G RAM specifications.

In Figure 5.3, the impact of the number of sensor nodes in a system, powered by 2 dedicated RF sources, is studied. Based on the optimal q^* *and* r^*, the energy harvesting time allocation provided by the proposed algorithm delivers a significant gain in the system average sum-throughput, as observed when the number of sensor nodes increases from 1 to 5.

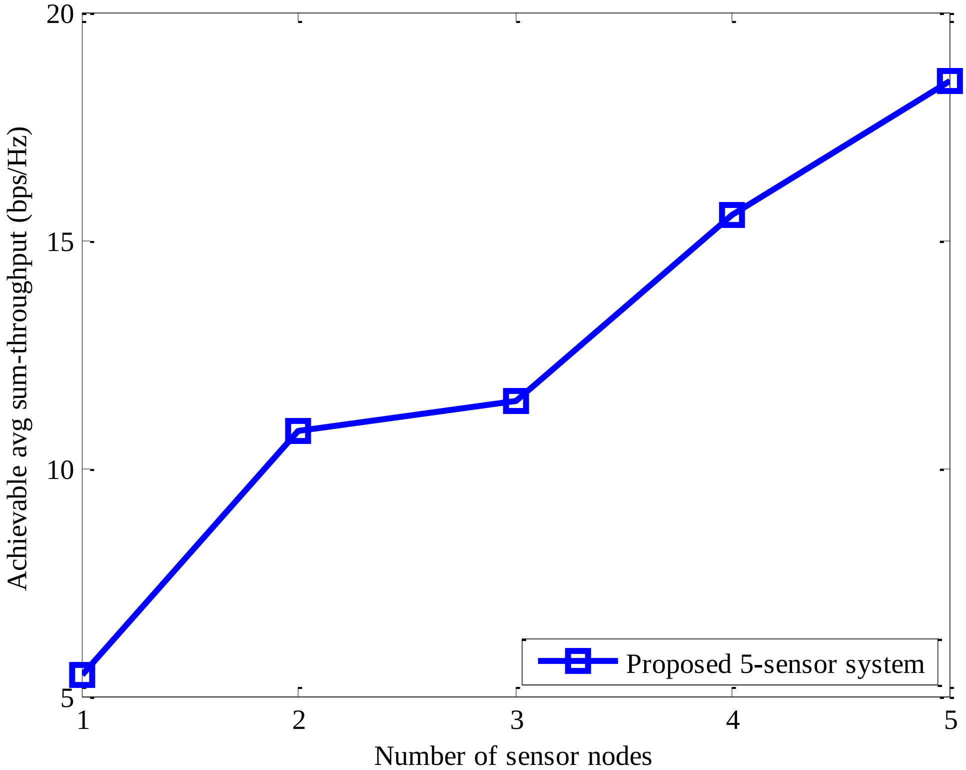

Figure 5.3. Achievable average sum-throughput versus number of sensor nodes. The solid blue lines with a square marker indicates a 5-sensor system.

In Figure 5.4, the impact of transmit power on the system's achievable sum-throughput in a 3-sensor system powered by 3 dedicated RF sources is investigated for 0.1 W, 1 W, and 3 W.

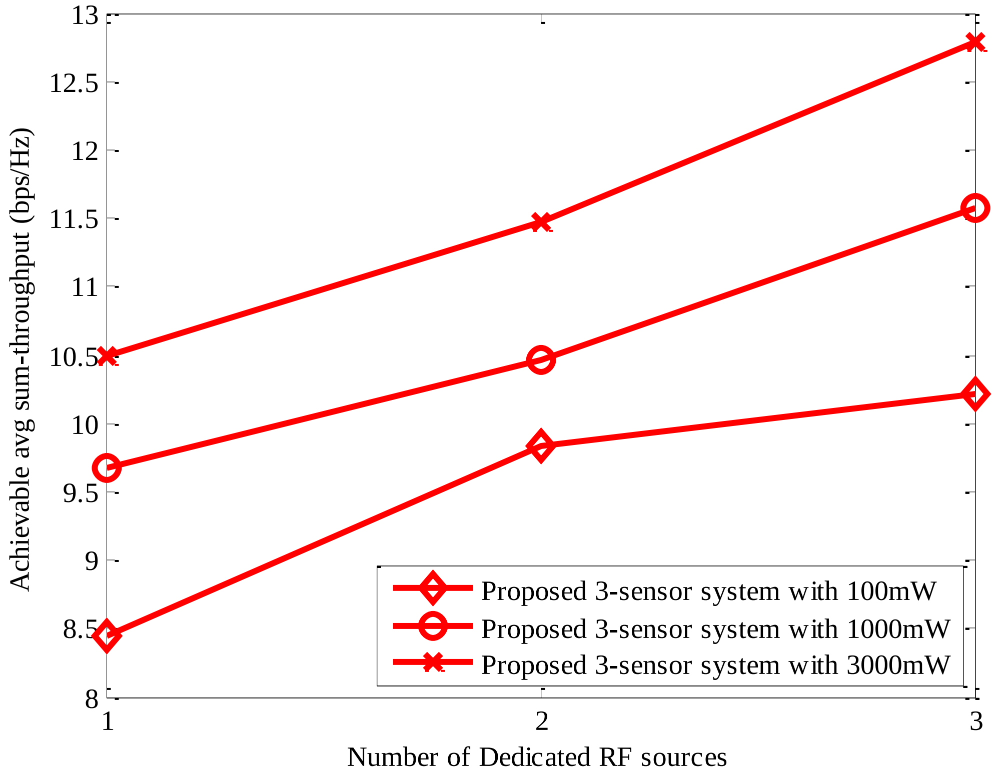

Figure 5.4. Achievable average sum-throughput versus transmit power. The red lines indicate a 3-sensor system.

A substantial increase in the system performance is observed when the transmission power of the dedicated RF sources was increased from 100 mW, 1000 mW to 3000 mW, which indicates that the transmission power of the dedicated RF sources has an influence on the system performance. As expected, a higher number of RF sources also increase the system performance. In the context of energy-efficient and sustainable network communications, the acceptable performance for transmission power as low as 100 mW is a significant result here.

The new WIPT system is compared with an existing state-of-the-art WIPT system proposed in [27] with respect to the achievable average sum-throughput, and including the fairness.

As in [204], a 2-sensor node system and a 3-sensor node system are considered. Both systems are powered by 5 dedicated RF sources. For the comparison, the same simulation software is run with either the proposed algorithm enabled for the WIPT system of this work, or disabled for the existing WIPT system. In Figures 5.5 and 5.6, the achievable average sum-throughput and Jain's fairness of the proposed WIPT systems is compared with the existing WIPT system.

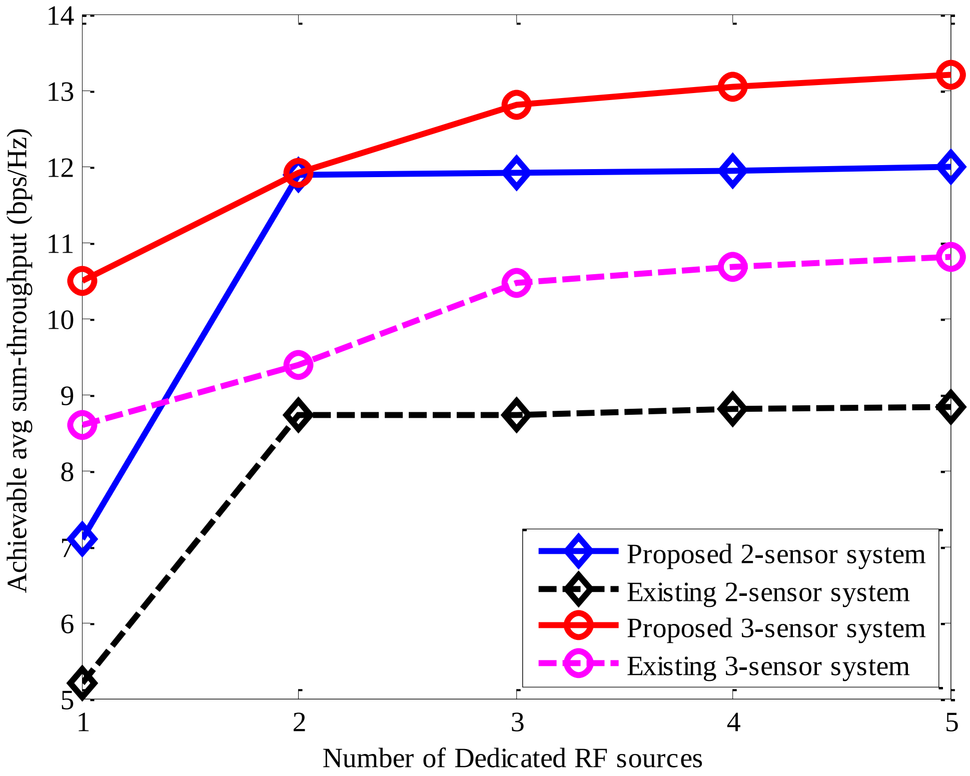

Figure 5.5. Achievable average sum-throughput versus number of dedicated RF sources. The blue lines indicate a 2-sensor system, while the red lines indicate a 3-sensor system. The solid lines represent the proposed, while the dashed lines represent the existing system [204].

Based on the newly proposed algorithm, the new WIPT system achieves a higher average sum-throughput compared to the existing WIPT system, due to optimal time allocation by the algorithm to energy harvesting and information transmission. From the results in Figure 5.5, it is seen that a 2-sensor system using the proposed algorithm performs comparably to a 3-sensor system using the existing algorithm. Furthermore, based on the formulated Jain's equation, the fairness among the sensor nodes in energy harvesting time and information transmission rate, is calculated. As shown in Figure 5.6, the new WIPT system provides an increased fairness compared to the existing 2-sensor node and 3-sensor node systems, indicating improvement in the problems associated with the doubly near-far problem.

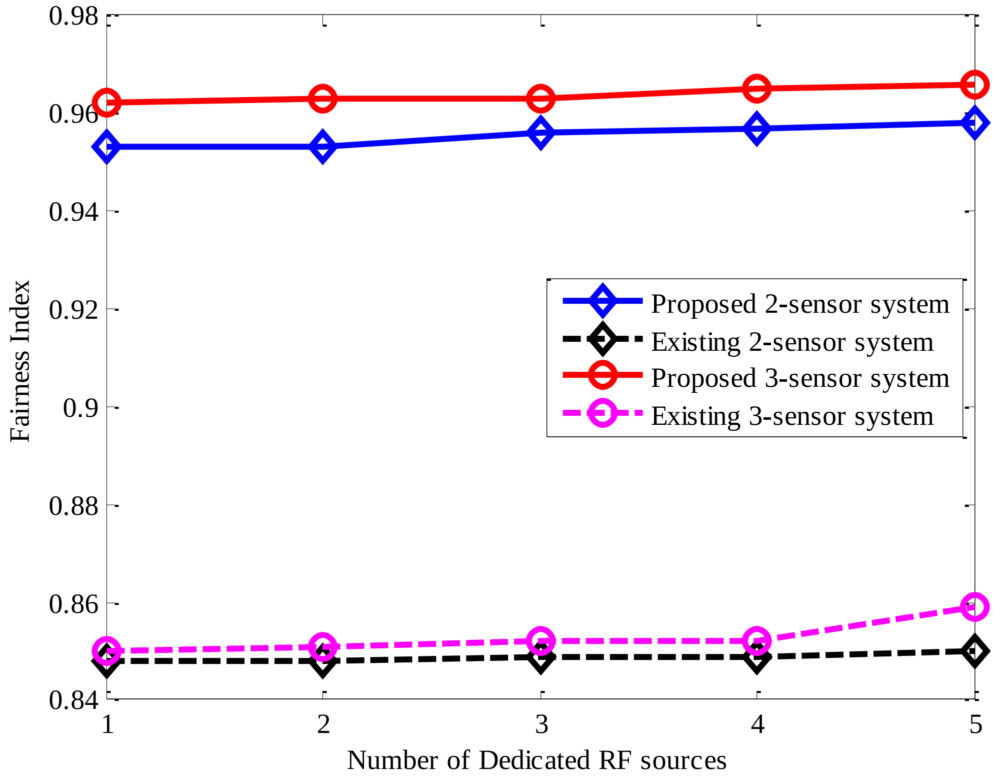

Figure 5.6. Fairness versus number of dedicated RF sources. The blue lines indicate a 2-sensor system, while the red lines indicate a 3-sensor system. The solid lines represent the proposed, while the dashed lines represent the existing system [204].

5.8 CHAPTER SUMMARY

This chapter has addressed the problem of unfairness in energy harvesting and information transmission rate issue among multiple sensor nodes in a multi-group WIPT system, known as the doubly near-far problem. The newly proposed multi-group WIPT system has revealed advantageous sum-throughput and fairness results by providing different optimal energy harvesting time and information transmission time to the randomly deployed sensor nodes, based on their calculated distances to dedicated RF sources and the sink node, using the proposed optimization algorithm.

In terms of transmission throughput rate results, a 2-sensor system using the newly proposed algorithm performs comparably to a 3-sensor system using an existing algorithm proposed in [204], with all other network parameters the same.

When the doubly near-far problem is encountered in network groups at different distances from the sink node, the transmission throughput rate of the proposed system doubles when compared to a system with the same configuration, but without the proposed optimization algorithm. Also, in the context of energy-efficient and sustainable network communications, the acceptable performance of the proposed WIPT network system for transmission power as low as 100 mW is a significant result.

For emphasis purposes, this chapter has addressed the improvement of the energy utilization, throughput and fairness performances of a WQM system that employs a random deployment strategy.

CHAPTER 6 CONCLUSION

Recently, wireless sensor network technology has attracted the research community in WQM applications based on its promises to efficiently and timely monitor WQ and its parameters as against the conventional methods which are confronted with several shortcomings. Without any iota of doubt, wireless sensor network technology is envisaged to be a frontline solution in the space of water monitoring applications in the future generation. For this dream to ever come true, it is essential to carry out comprehensive and thorough investigations into the strategies that will enable wireless sensor network in WQM to efficiently and optimally utilize its limited and scarce resources in achieving the diverse requirements of WQM applications, for example, sustainable network operation, energy efficiency, low-cost, efficient WQ data communication, and timely and reliable delivery of WQ data. The need to satisfy the requirements of wireless sensor network in WQM applications has created a scope for a gap in knowledge. Unfortunately, enough work has not been done in addressing the stumbling blocks to the productivity of wireless sensor network solutions in WQM, then the necessity to address the presented research work emerged in this thesis. It is worth mentioning that the investigations carried out in this research study, including the findings that are presented, form a concise and cogent solution to various open research issues in wireless sensor network for WQM.

For consistency purposes, the reporting of this thesis has been based on the fundamental principles that governs the presentation of technical reports in logical manners in the domain of engineering, wireless networks and wireless communications fields. Importantly, this concluding section presents a summary of the key ideas that are introduced, essential findings, and important contributions to knowledge, as discussed in the previous chapters of this thesis

In Chapter 1, a concise introduction that gives insightful details about the research study is provided. The chapter as well established the exact problem definition and investigates the limiting barriers to the productivity of wireless sensor network in WQM. Investigations were also carried out on the development of solutions that are viable to the identified problems in the chapter. Based on the developments, the chapter already have a clear direction, including the objectives to be achieved by the research study. Also, in Chapter 1, the contributions of the research work, including the research outputs that resulted from the research, were highlighted.

In Chapter 2, an in-depth background knowledge on the research work through a detailed and comprehensive survey on wireless sensor network for WQM was provided. The chapter addressed the relevant aspects of wireless sensor network in WQM including the recent works on the subject matter in the literature. Through the survey, the areas of wireless sensor network in WQM that have been well addressed were revealed, while the limiting barriers (such as energy scarcity and consumption problems) to the optimal productiveness and usefulness of several wireless sensor network solution models were also uncovered. To seek solutions to the identified limiting barriers to the wireless sensor network systems, various solutions were analysed and this provides an essential direction in addressing the shortcomings of wireless sensor network in WQM. In the chapter, an exhaustive survey regarding energy efficient solutions for wireless sensor systems particularly for wireless sensor network in WQM was carried out. Examples of such solutions are energy harvesting solution models and energy optimization methods. Through this research effort, a viable and sustainable RF power solution was identified as well as efficient optimization methods including linear programming and Lagrangian techniques.

In Chapter 3, the development and analysis of models that addressed the problems of energy scarcity and energy consumption in wireless sensor network for WQM were investigated.

The chapter introduced the concept of multi-network and multi-energy-resource as an appealing strategy to seek solutions to the energy problems, which are long-standing barriers to wireless sensor networks. In the chapter, a fundamental doubly-near-far problem is encountered in the developed wireless sensor network for WQM. The identified problems are significant issues that confront the effectiveness of the wireless sensor networks in WQM applications. Through the exploration of the introduced concept, the energy problems and the doubly-near-far problem are effectively tackled. In the chapter, RF energy solution and optimization strategies were coupled with the proposed system model to address the scarceness in the availability of energy in the network, and also to optimize the precious network resource utilization to improve fairness in resource allocation improve and the efficiency of the system. To validate the proposed system, the system was extensively analysed, evaluated, and compared with the existing state-of-the-art systems and the new system performance gains significantly outperforms the existing systems. As an example, when k is set to two with one dedicated radio frequency energy source, the proposed system produced an average sum-throughput of 8.44 bps/Hz and a fairness index of 0.992, while the data published in [204] for the existing systems are an average sum-throughput of 6.18 bps/Hz and a fairness index of 0.876. These results represent significant improvements of 36% in the system throughput rate, and 13% in the fairness index. Also, when k is set to three with a dedicated radio frequency energy source of one, the proposed system produced an average sum-throughput of 12.11 bps/Hz and a fairness index of 0.992, while the published data for the existing system are an average sum-throughput of 10.07 bps/Hz and a fairness index of 0.876 [204]. These results represent significant improvements of 20% in the system throughput rate, and 13% in the fairness index. Also, the introduced concept has assisted in tackling the limiting effects of the energy problems to the productivity of wireless sensor network, thus obtaining solutions that enhance the resourcefulness of wireless sensor network in WQM in terms of sustainable network operation, fairness in energy resource allocation, throughput rate, and optimal utilization of the network resources as shown in Figures 3.5, 3.6, 3.7, 3.8, 3.9, and 3.10. The multi-network concept was also employed to seek solutions to the unfairness problem in resource allocation in a wireless powered sensor network.

In Chapter 4, the concept of network heterogeneity was introduced to address the network requirements of the wireless sensor network for WQM and to as well find optimal solutions to the problems of energy scarcity, energy consumption, and resource allocation. To address the mentioned problems, optimal optimization strategies were developed through the exploitation of problem structure exploration, convex optimization, partial derivative techniques to optimize the process of network resource allocation and utilization in a heterogeneous multi-class and multiple resource wireless transmission system that focused on monitoring water and its quality. Also, radio frequency energy harvesting from dedicated radio frequency power sources was introduced and combined with the proposed system to address the issue of energy scarcity. Through the developed optimization methods, the sum-throughput of the new WQM system was maximized to reduce the system energy consumption and enhance the system overall throughput rate. The validation of the new system was thoroughly carried out through comparison with the state-of-the-art systems in [204] to investigate the efficiency and performance gains of the proposed system. Based on the thorough investigations through extensive analysis and evaluation, the new system significantly improved over the existing systems and has a lower computational complexity. For example, when two systems including a two-sensor system and a three-sensor system which were powered by five intended radio frequency power sources, were compared with the existing systems of the same configurations, the new system had sum-throughput improvements of 26.46 % and 27.18 % for two-sensor and three-sensor respectively, and improvements of 8.6 % and 8.5 % for two-sensor and three-sensor respectively for resource allocation fairness. The improvements in the attainable sum-throughput and resource allocations results are due to the efficiency the newly proposed algorithm. Also, it is importance to emphasize that the application of the introduced concept has helped to seek optimal solutions to the said problems that hinder the resourcefulness of wireless sensor network in WQM as described by Figures 4.6, 4.7, 4.8, 4.9, 4.10, 4.11, and 4.12.

In Chapter 5, the concept of multi-group and multi-source system was introduced to address energy problems and the unfairness issue in resource allocation among the WQ sensors in a wireless sensor network system dedicated to the monitoring of WQ. The aforementioned problems are great limiting barriers that hinder the resourcefulness of wireless sensor network in WQM. The newly introduced concept was employed to effectively seek holistic solutions to the problems. In the chapter, optimization strategies were employed to develop energy efficient solutions to maximize the fairness in energy harvesting and WQ information transmission throughput in the new multi-group wireless sensor network system devoted to the monitoring of WQ. The proposed solution was validated and compared with the related existing work. Also, the proposed system has contributed to improving the productivity of the efficiency of a wireless sensor system dedicated to WQM in terms the achievable throughput, fairness in energy resource allocation, sustainable network, and energy efficient communication as demonstrated in Figures 5.3, 5.4, 5.5, and 5.6.

This thesis has validated the solutions obtained to the developed system models through the simulation experiments and performance comparison with the results of the state-of-the-art related works in the literature for validation purposes.

6.1 RECOMMENDATIONS ON FUTURE RESEARCH DIRECTION

Based on the contributions of thesis to the body of knowledge on wireless sensor networks for WQM, it is evident that several miles have been covered in making wireless sensor networks deployment in WQM applications a successful venture. However, there are still rooms for further improvements that can be fruitfully investigated by the next generation of researchers to further push WQM sensor network system to unprecedented heights to improve their widely acceptance and deployments. For this reason, key recommendations have been drawn from the problems identified and addressed in this thesis, which are extensively detailed in the chapter 3, chapter 4, and chapter 5.

6.1.1 Recommendations on improving the energy harvesting efficiency of radio frequency energy harvesting water quality sensors

- The RF-to-DC (or rectifiers) currently used by the energy harvesting water quality sensors have a conversion efficiency of about 70% [1], [199], [200], while the matching circuit and the internal circuitry of the power converter are responsible for about 30% power loss. Since the RF-to-DC converters determines the amount of the usable DC power supply that is convertible from the radio frequency power received by the energy harvesting water quality sensors from a dedicated radio frequency power source and eventually made available to the water quality sensors, then there is a pressing need to improve the efficiency of the RF-to-DC converters in order to enhance the amount of harvestable radio frequency energy.

- Pragmatic techniques such as beamforming solutions for improving radio frequency energy transfer efficiency are envisaged as fruitful research efforts to improve the efficiency of the harvestable radio frequency power by the energy harvesting water quality sensors. Such efforts are promising strategies to enhance the performance gain of the wireless powered sensor network systems dedicated to water quality monitoring by powering the energy harvesting water quality sensors using energy beamforming.

6.1.2 Recommendations on wireless powered sensor network systems for water quality monitoring applications

- Currently, the conventional radios such as ZigBee and Bluetooth are the standard communication network solutions mostly employed in wireless network systems for WQM applications due to the fact that radio solutions are not suitable candidates for sensor network systems or the usable ones are presently at their nascent stage, for example the newly emerged low-power wide area network solutions including LoRa and Sigfox. Because of this, it is important to emphasize that the energy problems in wireless sensor network for WQM may be further tackled as a future research by introducing low-power communication radios such as backscatter radios. The standard conventional radios need to generate active radio frequency for data communication purposes and the radio frequency components in them which are used in the process of radio frequency waves generation consumes a significant amount of power. So, by exploiting the usage of backscatter radios, reasonable power may be saved as the radio frequency signals in the environment of the wirelessly powered water quality sensors may be fruitfully exploited for data communication and energy harvesting purposes.

- The positive performance of the simulated systems in this thesis has provided promising predictions regarding the real-world performance of the proposed systems. Based on this, the study has provided a good future research baseline to further investigate the robustness of wirelessly powered WQM sensor network systems against the failure of a component in the system. Such a research effort would be useful to study the possibility of any trade-off in optimality and robustness.

6.1.3 Recommendations on the exploitation of optimization methods

- This study has produced a thorough review of the useful and relevant optimization methods that may be potentially exploited in WQM sensor network systems to optimize various limited network resources for a judicious utilization. Also, it has been established that a single optimization method may not fully provide what it takes to address an optimization problem due to the possibilities of different requirements and constraints that are captured in a system model. This has provided a context for the exploitation of different optimization strategies as each of the strategy has its own strengths and weaknesses. A few, but critical optimization methods have been fruitfully harnessed in this study in addressing energy issues. As a consequence, an interesting future area of research is to explore some the optimization methods that have been detailed in this thesis to further deal with energy constraints in the WQM sensor network systems.

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ADDENDUM A OPTIMIZING ENERGY AND THROUGHPUT OF A WATER-QUALITY MONITORING SYSTEM

A.1 PROOF OF CONVEXITY FOR PROBLEM P1 TRANSFORMATION

The optimization problem (P1) in (3.21) is a non-convex problem because R_{sum} contains a *log* function. The transformation of (P1) to a convex problem was achieved through the application of the Lagrangian dual decomposition method to obtain a new problem (P1′). The Lagrangian of (3.21) is given as follows:

From (3.10) and (3.18),

$$R_n\,(q,\beta) = \frac{\beta_n}{\mathrm{In}2}\,\mathrm{In}\left(1 + \alpha_n \frac{\sum_{g=1}^{G} q_g}{\beta_n}\right), n = 1, \dots, N \tag{A1}$$

$$R_m\,(r,\Psi) = \frac{\Psi_m}{\mathrm{In}2}\,\mathrm{In}\left(1 + \gamma_m \frac{\sum_{g=1}^{G} r_g}{\Psi_m}\right), m = 1, \dots, M \tag{A2}$$

where:

$$q = q_1, q_2, \dots, q_G, \beta = \beta_1, \beta_2, \dots, \beta_N$$

$$r = r_1, r_2, \dots, r_G, \Psi = \Psi_1, \Psi_2, \dots, \Psi_M$$

The sum-throughput of all sensor nodes *n* and *m*, that is, $R_{n,m}$ or R_{sum} is:

$$R_{n,m}\,(q,\beta,r,\psi) = \sum_{n=1}^{N} R_n\,(q,\beta) + \sum_{m=1}^{M} R_m\,(r,\psi)$$

To show that (P1) is concave, let the Lagrangian multiplier be λ, where $\lambda \geq 0$ is associated to constraint (3.22). The Lagrangian of (P1) is given by (P1′).

(P1′)

$$L(q,r,\beta,\Psi,\lambda) = R_{n,m}\,(q,r,\beta,\Psi) + \lambda\left(\sum_{g=1}^{G} q_g + \sum_{g=1}^{G} r_g + \sum_{n=1}^{N} \beta_n + \sum_{m=1}^{M} \Psi_m - 1\right)$$

Substituting (A1) and (A2) into (P1′) gives:

$$L(q,r,\beta,\Psi,\lambda) = \frac{\beta_n}{\text{In}2}\,\text{In}\left(1 + \alpha_n \frac{\sum_{g=1}^{G} q_g}{\beta_n}\right) + \frac{\Psi_m}{In2}\,In\left(1 + \gamma_m \frac{\sum_{g=1}^{G} r_g}{\Psi_m}\right)$$
$$\lambda\left(\sum_{g=1}^{G} q_g + \sum_{g=1}^{G} r_g + \sum_{n=1}^{N} \beta_n + \sum_{m=1}^{M} \Psi_m - 1\right) \qquad \text{(A3)}$$

By applying the Karush–Kuhn–Tucker (KKT) conditions to (A3), the following must hold:

$$\frac{\partial L}{\partial q_g} = 0; \frac{\partial L}{\partial \beta_n} = 0; \frac{\partial L}{\partial r_g} = 0; \frac{\partial L}{\partial \Psi_m} = 0\ ;$$

Solving for $\frac{\partial L}{\partial q_g} = 0$, find the derivative of L with respect to q_g,

$$L(q,r,\beta,\Psi,\lambda) = \frac{\beta_n}{\text{In}2}\,\text{In}\left(1 + \alpha_n \frac{\sum_{g=1}^{G} q_g}{\beta_n}\right) + \lambda\left(\sum_{g=1}^{G} q_g\right) \qquad \text{(A4)}$$

$$\frac{\partial L}{\partial q_g} = \frac{\beta_n \alpha_n G}{\text{In}2\left(\beta_n+\alpha_n \sum_{g=1}^{G} q_g\right)} + \lambda G \quad \text{(A5)}$$

Solving for $\frac{\partial L}{\partial r_g} = 0$, find the derivative of L with respect to r_g,

$$L(q,r,\beta,\Psi,\lambda) = \frac{\Psi_m}{\text{In}2} \text{In}\left(1+\gamma_m \frac{\sum_{g=1}^{G} r_g}{\Psi_m}\right) + \lambda\left(\sum_{g=1}^{G} r_g\right) \quad \text{(A6)}$$

$$\frac{\partial L}{\partial r_g} = \frac{\Psi_m \gamma_m G}{\text{In}2\left(\Psi_m+\gamma_m \sum_{g=1}^{G} r_g\right)} + \lambda G \quad \text{(A7)}$$

Solving for $\frac{\partial L}{\partial \beta_n} = 0$, find the derivative of L with respect to β_n,

$$L(q,r,\beta,\Psi,\lambda) = \frac{\beta_n}{\text{In}2} \text{In}\left(1+\alpha_n \frac{\sum_{g=1}^{G} q_g}{\beta_n}\right) + \lambda\left(\sum_{n=1}^{N} \beta_n\right) \quad \text{(A8)}$$

$$\frac{\partial L}{\partial \beta_n} = \frac{1}{\text{In}2} \text{In}\left(1+\alpha_n \frac{\sum_{g=1}^{G} q_g}{\beta_n}\right) + \frac{1}{\text{In}2} \frac{\beta_n \alpha_n G}{\beta_n+\alpha_n \sum_{g=1}^{G} q_g} \quad \text{(A9)}$$

Solving for $\frac{\partial L}{\partial \Psi_m} = 0$, find the derivative of L with respect to Ψ_m,

$$L(q,r,\beta,\Psi,\lambda) = \frac{\Psi_m}{\text{In}2} \text{In}\left(1+\gamma_m \frac{\sum_{g=1}^{G} r_g}{\Psi_m}\right) + \lambda\left(\sum_{m=1}^{M} \Psi_m\right) \quad \text{(A10)}$$

$$\frac{\partial L}{\partial \Psi_m} = \frac{1}{\text{In}2} \text{In}\left(1+\gamma_m \frac{\sum_{g=1}^{G} r_g}{\Psi_m}\right) + \frac{1}{\text{In}2} \frac{\Psi_m \gamma_m G}{\Psi_m+\gamma_m \sum_{g=1}^{G} q_g} \quad \text{(A11)}$$

Solving for $\frac{\partial L}{\partial \lambda} = 0$, find the derivative of L with respect to λ,

$$L(q,r,\beta,\Psi,\lambda) = \lambda\left(\sum_{g=1}^{G} q_g + \sum_{g=1}^{G} r_g + \sum_{n=1}^{N} \beta_n + \sum_{m=1}^{M} \Psi_m - 1\right) \quad \text{(A12)}$$

$$\frac{\partial L}{\partial \lambda} = \left(\sum_{g=1}^{G} q_g + \sum_{g=1}^{G} r_g + \sum_{n=1}^{N} \beta_n + \sum_{m=1}^{M} \Psi_m - 1\right) \quad \text{(A13)}$$

Thus, (P1′) is a concave optimization problem. Consequently, any convex optimization method can be employed to address (P1′).

A.2 PROOF OF ENERGY-HARVESTIN UNFAIRNESS MINIMIZATION

From constraint (3.28):

$$\sum_{g=1}^{G} q_g + \sum_{g=1}^{G} r_g = 1 \quad \text{(A14)}$$

we have,

$$\sum_{g=1}^{G} P_{A,g}\, b_n q_g + \sum_{g=1}^{G} P_{A,g}\, h_m r_g \quad \text{(A15)}$$

Putting (A15) in (3.4) and (3.16) gives:

$$E_{n,m} = \eta_n \sum_{g=1}^{G} P_{A,g}\, b_n q_g + \eta_m \sum_{g=1}^{G} P_{A,g}\, h_m r_g,\ n = 1, 2, \ldots, N,\ m = 1, 2, \ldots, M \quad \text{(A16)}$$

Let $E^*_{n,m}$ be the optimal values for E_n and E_m due to q^*_g and r^*_g.

Since q^*_g and r^*_g represent the optimal values for q_g and r_g. Therefore, from (A16), we have:

$$E^*{}_{n,m} = \eta_n \sum_{g=1}^{G} P_{A,g}\, b_n q^*_g + \eta_m \sum_{g=1}^{G} P_{A,g}\, h_m r^*_g,\ n = 1, 2, \ldots, N,\ m = 1, 2, \ldots, M \quad \text{(A17)}$$

From (A17), q^*_g and r^*_g give optimal values for subsequent values of $E^*_{n,m}$.

ADDENDUM B EFFICIENT ENERGY RESOURCE UTILIZATION IN A WIRELESS SENSOR SYSTEM FOR WATER QUALITY MONITORING

B.1 PROOF OF CONVEXITY FOR PROBLEM P3 TRANSFORMATION

The parameters of (4.21) such as log function, rendered the optimization problem as a non-convex function, and it was transformed through problem structure exploration technique by changing variable $t_c\xi_0$ to $\xi_{0,c}$, and obtaining the natural log of the log function in (4.9) and (4.18) respectively, to obtain a new problem (P4). From (4.9) and (4.18), (4.27) and (4.28) were derived as follows:

$$R_a\ (j,\zeta) = \frac{\zeta_a}{\text{In}2}\text{In}\left(1+\alpha_a\frac{\sum_{c=1}^{C} j_c}{\zeta_a}\right), \forall\ a = 1,2,\dots,A \tag{B1}$$

$$R_b\ (\xi) = \frac{\xi_b}{\text{In}2}\text{In}\left(1+\gamma_b\frac{\sum_{c=1}^{C} \xi_{0,c}}{\xi_b}\right), \forall\ a = 1,2,\dots,B \tag{B2}$$

where:

$$j = j_1, j_2, \dots, j_C,\ \zeta = \zeta_1, \zeta_2, \dots, \zeta_A\ \ and$$

$$\xi = \xi_{0,1}, \xi_{0,2}, \dots, \xi_{0,M}, \xi_1, \xi_2, \dots, \xi_B$$

The sum-throughput of the overall sensor nodes in Class A and Class B, which is defined by $R_{a,b}$ is:

$$R_{a,b}\ (j, \zeta, \xi) = \sum_{a=1}^{A} R_a(j, \zeta) + \sum_{b=1}^{B} R_b(\xi) \qquad \text{(B3)}$$

Consequently, the optimization problem (P3) is transformed to a new problem defined as (P4).

(P4):

$$\max_{j,\zeta,\xi} R_{a,b}\ (j, \zeta, \xi) \qquad \text{(B4)}$$

s.t:

$$\sum_{c=1}^{C} j_c + \sum_{c=1}^{C} \xi_{0,c} + \sum_{a=1}^{A} \zeta_a + \sum_{b=1}^{B} \xi_b \leq 1 \qquad \text{(B5)}$$

$$j_c \geq 0, \forall\ c = 1, 2, .., C \qquad \text{(B6)}$$

$$\zeta_a \geq 0, \forall\ a = 1, 2, .., A \qquad \text{(B7)}$$

$$\xi_b \geq 0, \forall\ b = 1, 2, .., B \qquad \text{(B8)}$$

The concavity of problem (P4) is shown as follows through the application of partial derivative

$$R_{a,b}\ (j, \zeta, \xi) = \frac{\zeta_a}{\mathrm{In2}} In\left(1 + \alpha_a \frac{\sum_{c=1}^{C} j_c}{\zeta_a}\right) + \frac{\xi_b}{\mathrm{In2}} In\left(1 + \gamma_b \frac{\sum_{c=1}^{C} \xi_{0,c}}{\xi_b}\right) \qquad \text{(B9)}$$

The second derivative of $R_{a,b}$ (j, ζ, ξ) and j_c is:

$$\frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial {j_c}^2} = \frac{-\ \alpha_a^2 \zeta_a}{\text{In}2\left(\zeta_a + \alpha_a \sum_{c=1}^{C} j_c\right)^2} \tag{B10}$$

Since α_a^2, I$n2$, and $(\zeta_a + \alpha_a \sum_{c=1}^{C} j_c)$ are positive, then,

$$\frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial {j_c}^2} = \frac{-\ \alpha_a^2 \zeta_a}{\text{In}2\left(\zeta_a + \alpha_a \sum_{c=1}^{C} j_c\right)^2} \leq 0 \tag{B11}$$

if $\zeta_a \geq 0$. Hence, $R_{a,b}$ (j, ζ, ξ) is concave with respect to j_c .

The second derivative of $R_{a,b}$ (j, ζ, ξ) vis-à-vis $\xi_{0,c}$ gives:

$$\frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial {\xi_{0,c}}^2} = \frac{-\ \gamma_b^2 \xi_b}{\text{In}2\left(\xi_b + \gamma_b \sum_{c=1}^{C} \xi_{0,c}\right)^2} \tag{B12}$$

Since γ_b^2, I$n2$, and $\left(\xi_b + \ \gamma_b \sum_{c=1}^{C} \xi_{0,c}\right)$ are positive, then,

$$\frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial {\xi_{0,c}}^2} = \frac{-\ \gamma_b^2 \xi_b}{\text{In}2\left(\xi_b + \gamma_b \sum_{c=1}^{C} \xi_{0,c}\right)^2} \leq 0 \tag{B13}$$

if $\xi_b \geq 0$. Hence, $R_{a,b}$ (j, ζ, ξ) is concave with respect to $\xi_{0,c}$.

The second derivative of $R_{a,b}$ (j, ζ, ξ) and ζ_a gives:

$$\frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial {\zeta_a}^2} = \frac{-\alpha_a}{\zeta_a^2 \text{In}2}\left(1 + \alpha_a \frac{\sum_{c=1}^{C} j_c}{\zeta_a}\right)^{-2} . \left(\sum_{c=1}^{C} j_c\right)^2 \tag{B14}$$

Also, the second derivative of $R_{a,b}$ (j, ζ, ξ) and ξ_b gives:

$$\frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial \xi_b{}^2} = \frac{-\gamma_b}{\xi_b^2 \mathrm{In}2}\left(1+\gamma_b \frac{\sum_{c=1}^{C} \xi_{0,c}}{\xi_b}\right)^{-2} . \left(\sum_{c=1}^{C} \xi_{0,c}\right)^2 \quad \text{(B15)}$$

$$\frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial j_c\, \partial \zeta_a} = \frac{\alpha_a^2}{\zeta_a^2 \mathrm{In}2}\left(1+\alpha_a \frac{\sum_{c=1}^{C} j_c}{\zeta_a}\right)^{-2} . \sum_{c=1}^{C} j_c \quad \text{(B16)}$$

$$\frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial \xi_{0,c}\, \partial \xi_b} = \frac{\gamma_b^2}{\xi_b^2 \mathrm{In}2}\left(1+\gamma_b \frac{\sum_{c=1}^{C} \xi_{0,c}}{\xi_b}\right)^{-2} . \sum_{c=1}^{C} \xi_{0,c} \quad \text{(B17)}$$

$$\frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial j_c\, \partial \xi_b} = 0; \quad \frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial \xi_{0,c}\, \partial \zeta_a} = 0; \frac{\partial^2 R_{a,b}\ (j,\zeta,\xi)}{\partial \zeta_a\, \partial \xi_b} = 0; \quad \text{(B18)}$$

From the second derivative test, $R_{a,b}\ (j, \zeta, \xi)$ is a concave function and it can be solved through any known standard convex method.

B.2 MINIMIZATION OF ENERGY HARVESTING UNFAIRNESS

Using (4.22a), that is:

$$\sum_{c=1}^{C} j_c + \sum_{c=1}^{C} t_c = 1 \quad \text{(B19)}$$

$$\text{If } \sum_{c=1}^{C} P_c\, n_a j_c + \sum_{c=1}^{C} P_c\, u_b t_c\, \xi_0 = \sum_{c=1}^{C} P_c\, n_a j_c + \xi_0 \sum_{c=1}^{C} P_c\, u_b t_c \quad \text{(B20)}$$

Then, (B19) is true.

By substituting (B20) in (4.4) and (4.15), (B21) is derived as:

$$E_{a,b} = \varepsilon_a \sum_{c=1}^{C} P_c\, n_a j_c + \varepsilon_b \xi_0 \sum_{c=1}^{C} P_c\, u_b t_c,\ a = 1,2,\ldots,A,\ b = 1,2,\ldots, B \quad \text{(B21)}$$

Let $E_{a,b}^*$ be the optimal value for E_a and E_b due to j_c^*, t_c^*, and ξ_0^* .

Since j_c^* represents the optimal value for j_c , while t_c^* and ξ_0^* represents the optimal values for t_c and ξ_0. Therefore, from (B21), we have:

$$E^*_{a,b} = \varepsilon_a \sum_{c=1}^{C} P_c\, n_a j^*_c + \varepsilon_b \xi^*_0 \sum_{c=1}^{C} P_c\, u_b t^*_c,\ a = 1,2,\ldots,A,\ b = 1,2,\ldots,\ B \qquad \text{(B22)}$$

From (B22), j^*_c remains constant. Similarly, t^*_c remains constant regardless of ξ^*_0.

ADDENDUM C MAXIMIZING THE THROUGHPUT AND FAIRNESS OF A WATER QUALITY MONITORING WIRELESS SENSOR SYSTEM

C.1 PROOF OF CONVEXITY FOR PROBLEM P6 TRANSFORMATION

The optimization problem in (5.22) is a non-convex problem because R_{sum} contains a log function. The transformation of (P6) to a convex optimization problem was obtained by changing variable $q_g\beta_0$ to $\beta_{0,g}$, $r_g\Psi_0$ to $\Psi_{0,g}$, and obtaining the natural *log* of the *log* function in (5.9) and (5.19) respectively, to obtain a new problem (P7). From (5.9) and (5.19), (C1) and (C2) were derived as follows:

$$R_n\ (\beta) = \frac{\beta_n}{\mathrm{In2}} In\left(1 + \alpha_n \frac{\sum_{g=1}^{G} \beta_{0,g}}{\beta_n}\right), n = 1,2, \dots, N \tag{C1}$$

$$R_m\ (\Psi) = \frac{\Psi_m}{\mathrm{In2}} In\left(1 + \gamma_m \frac{\sum_{g=1}^{G} \Psi_{0,g}}{\Psi_m}\right), m = 1,2, \dots, M \tag{C2}$$

where:

$$\beta_{0,1}, \beta_{0,2}, \dots, \beta_{0,G}, \beta_1, \beta_2, \dots, \beta_N \ \ and$$

$$\Psi = \Psi_{0,1}, \Psi_{0,2}, \dots, \Psi_{0,M}, \Psi_1, \Psi_2, \dots, \Psi_M$$

The sum-throughput of all sensor nodes *n* and *m*, that is, $R_{n,m}$ or R_{sum} is:

$$R_{sum}\ (\beta, \Psi) = \sum_{n=1}^{N} R_n(\beta) + \sum_{m=1}^{M} R_m(\Psi) \qquad \text{(C3)}$$

Therefore, problem (P6) in (5.20) is transformed to:

(P7)

$$\max_{\beta,\Psi} R_{n,m}\ (\beta, \Psi) \qquad \text{(C4)}$$

subject to:

$$\sum_{g=1}^{G} \beta_{0,g} + \sum_{g=1}^{G} \Psi_{0,g} + \sum_{n=1}^{N} \beta_n + \sum_{m=1}^{M} \Psi_m \leq 1 \qquad \text{(C5)}$$

$$\beta \geq 0 \qquad \text{(C6)}$$

$$\Psi \geq 0 \qquad \text{(C7)}$$

Proof for (P7) convexity

$$R_{n,m}(\beta, \Psi) = \frac{\beta_n}{\text{In2}} In\left(1 + \alpha_n \frac{\sum_{g=1}^{G} \beta_{0,g}}{\beta_n}\right) + \frac{\Psi_m}{\text{In2}} In\left(1 + \gamma_m \frac{\sum_{g=1}^{G} \Psi_{0,g}}{\Psi_m}\right) \qquad \text{(C8)}$$

In (C8), taking the second derivative of $R_{n,m}(\beta, \Psi)$ with respect to $\beta_{0,g}$ gives:

$$\frac{\partial^2 R_{n,m}(\beta,\Psi)}{\partial(\beta_{0,g})^2} = \frac{-\alpha_n^2\ G^2\beta_n}{In2\left(\beta_n+\alpha_n \sum_{g=1}^{G} \beta_{0,g}\right)^2} \tag{C9}$$

Since α_n^2, G^2, $In2$ and $\left(\beta_n + \alpha_n \sum_{g=1}^{G} \beta_{0,g}\right)^2$ are positive, therefore,

$$\frac{\partial^2 R_{n,m}(\beta,\Psi)}{\partial(\beta_{0,g})^2} = \frac{-\alpha_n^2\ G^2\beta_n}{In2\left(\beta_n+\alpha_n \sum_{g=1}^{G} \beta_{0,g}\right)^2} \leq 0 \tag{C10}$$

provided $\beta_n \geq 0$. Hence, $R_{n,m}(\beta,\Psi)$ is concave with respect to $\beta_{0,g}$.

Also, in (C8), taking the second derivative of $R_{n,m}(\beta,\Psi)$ with respect to $\Psi_{0,g}$ gives:

$$\frac{\partial^2 R_{n,m}(\beta,\Psi)}{\partial(\Psi_{0,g})^2} = \frac{-\Psi_m^2 G^2 \Psi_m}{In2\left(\Psi_m+\gamma_m \sum_{g=1}^{G} \Psi_{0,g}\right)^2} \tag{C11}$$

Since Ψ_m^2, G^2, $In2$, and $\left(\Psi_m + \gamma_m \sum_{g=1}^{G} \Psi_{0,g}\right)^2$ are positive, therefore,

$$\frac{\partial^2 R_{n,m}(\beta,\Psi)}{\partial(\Psi_{0,g})^2} = \frac{-\Psi_m^2 G^2 \Psi_m}{In2\left(\Psi_m+\gamma_m \sum_{g=1}^{G} \Psi_{0,g}\right)^2} \leq 0 \tag{C12}$$

provided $\Psi_m \geq 0$. Hence, $R_{n,m}(\beta,\Psi)$is concave with respect to $\Psi_{0,g}$.

Furthermore, in (C8), taking the second derivative of $R_{n,m}(\beta,\Psi)$ with respect to $\beta_{0,g}$ and $\Psi_{0,g}$ gives:

$$\frac{\partial}{\partial\beta_{0,g}}\left(\frac{\partial R_{n,m}(\beta,\Psi)}{\partial\Psi_{0,g}}\right) = \frac{\partial^2 R_{n,m}(\beta,\Psi)}{\partial\beta_{0,g}\,\partial\Psi_{0,g}} = 0 \tag{C13}$$

Therefore, $R_{n,m}(\beta, \Psi)$ is concave with respect to $\beta_{0,g}$ and $\Psi_{0,g}$. Thus, (P7) is a concave optimization problem. Consequently, any convex optimization method can be applied to (P7).

C.2 PROOF OF ENERGY HARVESTING UNFAIRNESS MINIMIZATION

Using the constraint in (5.23a), that is:

$$\sum_{g=1}^{G} q_g + \sum_{g=1}^{G} r_g = 1 \qquad \text{(C14)}$$

Equation (C14) is true provided the following is true

$$\sum_{g=1}^{G} P_{A,g}\, b_n q_g\, \beta_0 + \sum_{g=1}^{G} P_{A,g}\, h_m r_g\, \Psi_0 = \beta_0 \sum_{g=1}^{G} P_{A,g}\, b_n q_g + \Psi_0 \sum_{g=1}^{G} P_{A,g}\, h_m r_g \qquad \text{(C15)}$$

Putting (C15) in (5.4) and (5.14) gives:

$$E_{n,m} = \eta_n \beta_0 \sum_{g=1}^{G} P_{A,g}\, b_n q_g + \eta_m \Psi_0 \sum_{g=1}^{G} P_{A,g}\, h_m r_g,\ n = 1,2,\ldots,N,\ m = 1,2,\ldots, M \qquad \text{(C16)}$$

Let $E_{n,m}^*$ be the optimal value for E_n and E_m due to q_g^*, β_0^* and r_g^*, Ψ_0^* .

Since q_g^* and β_0^* represents the optimal value for q_g and β_0 , while r_g^* and Ψ_0^* represents the optimal values for r_g and Ψ_0. Therefore, from (C16), we have:

$$E^*{}_{n,m} = \eta_n \beta_0^* \sum_{g=1}^{G} P_{A,g}\, b_n q_g^* + \eta_m \Psi_0^* \sum_{g=1}^{G} P_{A,g}\, h_m r_g^*,\ n = 1,2,\ldots,N,\ m = 1,2,\ldots, M \qquad \text{(C17)}$$

To determine the subsequent values of $E_{n,m}$ from (C16), the subsequent values of $E_{n,m}$ is represented by $E_{n,m,sub}$ and it is calculated using:

$$E_{n,m,sub} = \frac{E_n}{\beta_0} + \frac{E_m}{\Psi_0} = \eta_n \sum_{g=1}^{G} P_{A,g}\, b_n q_g + \eta_m \sum_{g=1}^{G} P_{A,g}\, h_m r_g,\ n = 1,2,\ldots,N,\ m = 1,2,\ldots,M \quad \text{(C18)}$$

Let $E^*_{n,m,sub}$ be the value of $E_{n,m,sub}$ due to optimal q_g^* and r_g^*, therefore, (C18) becomes:

$$E^*{}_{n,m,sub} = \eta_n \sum_{g=1}^{G} P_{A,g}\, b_n q_g^* + \eta_m \sum_{g=1}^{G} P_{A,g}\, h_m r_g^*,\ n = 1,2,\ldots,N,\ m = 1,2,\ldots,M \quad \text{(C19)}$$

Considering (C17) and (C19), it can be established that:

$$E^*{}_{n,m,sub}\beta_0^*\Psi_0^* = E^*{}_{n,m} \quad \text{(C20)}$$

From (C20), q_g^* and r_g^* remains constant regardless of β_0^* and Ψ_0^*.