Collaborative multimedia sensors for a connected and smart city

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Collaborative multimedia sensors for a connected and smart city

Capteurs multimédias collaboratifs pour une ville connectée et intelligente

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école doctorale sciences pour l'ingénieur et microtechniques

Collaborative multimedia sensors for a connected and smart city

Keywords: WVSNs, Network lifetime, Distributed algorithm, Data routing, Data processing, visual quality.

Abstract:

Wireless Video Sensor Networks (WVSN) are today considered as a promising technology, notably because of the availability of miniaturized multimedia hardware (e.g., CMOS cameras). Unlike traditional wireless sensor network (WSN), wireless multimedia sensor networks capture rich multimedia content (video, images, etc.). Because of the huge volume of multimedia data, particularly video data (the size of videos is far a way much more important than scalar data), on one hand and the limited resources of the sensor nodes on the other hand, deploying and managing a WMSN remain an active research field. In addition, multimedia data have the ability to be captured and delivered at different **visual quality** i.e., better the quality, lesser the encoding power (namely, the compression level) and higher the volume of the produced data. However, delivering high data rates will draw down the resources of the network, in particular the energy of nodes, as the latter are driven by batteries.

This dissertation mainly focuses on the network lifetime maximization problem while ensuring a distributed control and respecting the desired video quality at the end user. To do so, two main axes have been considered, namely, the data processing axis and data routing axis. The first axis tackles the problem of finding a trade-off between the encoding power at the source node and the desired video quality at the end user. While the second axis tackles the routing of the compressed data through the efficient existing paths.

Collaborative multimedia sensors for a connected and smart city

Mots-clés : RCVSF, Durée de vie du réseau, Algorithme distribué, Routage de données, Traitement de Données, Qualité visuel.

Résumé :

Les réseaux de capteurs vidéo sans fil (RCVSF) sont aujourd'hui considérés comme une technologie prometteuse, notamment en raison de la disponibilité du matériel multimédia miniaturisé (par exemple, les caméras CMOS). Contrairement aux réseaux de capteurs sans fil traditionnels (RCSFs), les réseaux de capteurs multimédias sans fil capturent un contenu multimédia volumineux (vidéo, images, etc.). En raison de l'énorme volume de données multimédias, en particulier des données vidéo (la taille des vidéos est beaucoup plus importante que les données scalaires), d'une part, et des ressources limitées des nœuds capteurs, d'autre part, le déploiement et la gestion d'un RCVSF restent un domaine de recherche très actif. Outre, les données multimédias peuvent être capturées et transmises à différentes **qualité visuelle** c.à.d, meilleure est la qualité, moins est la puissance d'encodage (à savoir, le niveau de compression) et plus est le volume des données générées. Cependant, le routage d'un débit élevé de données entraînera une baisse des ressources du réseau, en particulier de l'énergie des nœuds.

Cette thèse se focalise principalement sur le problème de maximisation de la durée de vie du réseau tout en assurant un contrôle distribué et en respectant la qualité vidéo souhaitée au niveau de l'utilisateur final. Dans cet ordre d'idées, deux axes principaux ont été considérés, à savoir l'axe de traitement de données et l'axe de routage de données. Le premier axe aborde le problème de trouver un compromis entre la puissance d'encodage au niveau du noeud source et la qualité vidéo souhaitée au niveau de la destination. Alors que le second axe aborde le routage de données compressées à travers les chemins existants.

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Abstract

Collaborative multimedia sensors for a connected and smart city

Nesrine KHERNANE
University of Bourgogne Franche-Comté, 2018

Supervisors: Ahmed MOSTEFAOUI and Jean-François COUCHOT

Due to their high application potential in various innovative fields (telemonitoring, telemedicine, etc.), Wireless Multimedia Sensor Networks (WMSN) arouse the interest of numerous research projects. In addition to inherent constraints of scalar sensor networks in terms of energy limitation, deployment, coverage, reliability, ..., WMSNs impose new constraints related to the captured data. Indeed, multimedia data are very voluminous in comparison to scalar data and, in addition, have a time constraint (real-time delivery). Moreover, their semantic content, very rich, is subject to different perceptions and interpretations depending on the quality of the acquisition. As a target application, this dissertation focuses on detecting available car parking spaces within a large city or a metropolis. Nevertheless, the proposed approaches can be used for a wide variety of WMSN applications for surveillance purposes.

In this context, the main objective remains the network lifetime maximization while ensuring an acceptable perceived quality at the destination station. The studied approaches are of a distributed nature for scalability reasons, required in WMSN. Two main axes have been targeted: **data processing** at source nodes and **data routing** toward the destination.

In the data processing axis, the main problem lies in the *quality* of the data to be transmitted. In general, the higher the quality is, the larger the data are, and consequently more important is the energy consumption and *vice versa*. It is therefore a question of finding a balance that preserve the energy resources; *i.e.* maximize the network lifetime while ensuring an acceptable quality of the sent data. The latter is the result of an encoding process at the source level.

Thus, we proposed a fully distributed algorithm that maximizes the network lifetime by optimally balancing the encoding power and the source rate at the source node in order to meet a desired visual quality at the destination level. In opposition to existing approaches, our algorithm, of distributed nature, is ensured to find such a trade-off whatever the initial network configuration is.

As a second step, we focused on data routing. In fact, due to the complexity of this problem, especially in a decentralized context, literature works have not considered jointly data processing and routing. In other words, routing was considered as a network input.

In the research work of this thesis, we have subsequently shown that the routing directly impacts the results of the network lifetime maximization process. Indeed, we have analyzed the behavior of several routing protocols in WMSN and the obtained results highlighted this influence. We have therefore proposed an analytic model integrating simultaneously the encoding of data at the source nodes and their routing to the base station. We have developed a semi-distributed resolution of this problem. The results obtained were very encouraging.

Thus, in the second part, a fully distributed solution was proposed, in which, the routing axis goal cannot be achieved without the parameters, that should be determined and updated by the data processing axis. On the other hand, the data processing axis goal cannot be achieved without the routing tables updated by the routing axis. The proposed solution allows: **a)** an end-to-end routing with local decisions at each video sensor node and **b)** the choose of the sufficient number of paths needed to ensure a reliable data transmission.

For the rest, we have completed our work by considering more realistic constraints, in particular the dynamic reliability of the links as well as the variation of their capacities (according to the remaining energy of the intermediate nodes). The simulation results showed that we had improved the network lifetime by 25%.

KEY WORDS: WMSN, Network lifetime, Distributed algorithm, Data routing, Data processing, visual quality.

RÉSUMÉ

Capteurs multimédias collaboratifs pour une ville connectée et intelligente

Nesrine KHERNANE
Université de Bourgogne Franche-Comté, 2018

Encadrants: Ahmed MOSTEFAOUI et Jean-François COUCHOT

En raison de leur fort potentiel applicatif dans différents domaines innovants (télésurveillance, télémédecine, etc.), les réseaux de capteurs multimédias sans fil (RCMSF) suscitent l'intérêt de nombreux travaux de recherche. Outre les contraintes soulevées par les réseaux de capteurs scalaires en termes de limitation d'énergie, de déploiement, de couvertures, de fiabilités,..., les RCMSF imposent de nouvelles contraintes liées à la nature même des données capturées et manipulées. En effet, les données multimédias sont sans aucune mesure très largement volumineuses en comparaison aux données scalaires et ont en plus une contrainte temporelle (temps-réel). De plus, leur contenu sémantique, très riche, est sujet à différentes perceptions, qui elles-mêmes dépendent de la qualité de l'acquisition. Dans le cadre de cette thèse, nous nous sommes intéressés à la problématique pratique d'un réseau de capteurs multimédias permettant de renseigner les automobilistes en temps réel sur les places de parking disponibles au niveau d'une ville, voire d'une agglomération. Cependant, de manière générale, les approches proposées dans nos travaux concernent tout RCMSF de surveillance.

Dans ce contexte, l'objectif principal reste de maximiser la durée de vie du réseau tout en assurant une qualité perçue acceptable au niveau de la station de traitement et ce sous un contrôle distribué (pour des raisons de passage à l'échelle évidentes). Deux axes sont à considérer : le traitement des données à la source et leur routage jusqu'à la station.

Dans l'axe traitement de données, le problème principal réside dans la « qualité » des données à transmettre. De manière générale, plus la qualité est importante, plus les données sont volumineuses et conséquemment la consommation énergétique est importante et vice-versa. Il s'agit donc de trouver un équilibre qui préserve les ressources énergétiques, c-à-d. maximiser sa durée de vie tout en assurant une qualité acceptable des données envoyées. Cette dernière est le résultat d'un processus d'encodage au niveau de la source.

Ainsi, nous avons d'abord abordé l'axe de traitement de données et proposé un algorithme complètement distribué qui maximise la durée de vie du réseau tout en assurant de manière optimale un équilibre entre la puissance d'encodage au niveau de la source et la qualité vidéo exigée au niveau de la destination. Contrairement aux approches existantes, notre algorithme, de nature distribuée, est assuré de trouver un tel compromis quelle que soit la configuration initiale du réseau.

En raison de la complexité de ce problème, notamment dans un contexte décentralisé, les travaux antérieurs n'ont traité que la partie traitement de données indépendamment du routage. En d'autres termes, le routage a été considéré comme une entrée.

Dans les travaux de recherche de cette thèse, nous avons par la suite montré que le routage impacte directement les résultats du processus de prolongation de la durée de vie du réseau. En effet, nous avons analysé le comportement de plusieurs protocoles de routage dans les RCMSF et les résultats obtenus ont mis en exergue cette influence. Nous avons donc proposé un modèle analytique intégrant de facto et le codage des données au niveau des sources et leur routage jusqu'à la station de traitement. Nous avons développé une résolution semi-distribuée de ce problème. Les résultats obtenus étaient très encourageants.

Ainsi, dans la deuxième partie, une solution entièrement distribuée a été proposée, dans laquelle, l'axe de routage ne peut pas être réalisé sans les paramètres déterminés et mis à jour par l'axe de traitement de données, et inversement. La solution proposée permet: a) un routage de bout en bout avec des décisions locales dans chaque nœud capteur et b) de déterminer le nombre suffisant de chemins nécessaires pour assurer une transmission fiable de données.

Pour la suite, nous avons complété nos travaux en considérant plus de contraintes réalistes, notamment la fiabilité des liens ainsi que la variation de leurs capacités (en fonction de l'énergie restante des nœuds intermédiaire). Les résultats de simulation ont montré une économie d'environs 25% de l'énergie totale.

KEY WORDS: RCMSF, Durée de vie du réseau, Algorithme distribué, Routage de données, Traitement de Données, Qualité visuel.

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ABBREVIATIONS

ADC ...... Analog to Digital Converter

a_{il}^{+} .... Matrix of the outgoing links

a_{il}^{-} .... Matrix of the incoming links

a_{il} .... General matrix of both outgoing and incoming links

AoV ...... Angle of View

B_i .... Initial energy of node i

BS .... Base station

CH .... Cluster Head

C_l .... The capacity of the link l

CMOS .... Complementary Metal-Oxide-Semiconductor

ComRange Communication Range

CS .... Camera Sensor

C_{total} ...... The average capacitance switched per cycle

D_h .... The distortion at node h

$\mathcal{D}_i$ .... The shortest distance from i to the sink.

f .... The clock speed

FoV ...... Field of View

$G(\mathcal{V}, \mathcal{L})$ ... An oriented graph

GNUM .... Generalized Network Utility Maximization

GPD ...... Gaussian Perturbation Distribution

GPS ...... Global Position System

I_0 .... The leakage current

$\mathcal{L}$ .... Set of oriented links

MEMS .... Microelectromechanical systems

MSE ...... Mean Squared Error

$\mathcal{N}$ .... Set of the multimedia sensors

n .... A processor dependent constant

N_{cyc} .... The number of clock cycles

$Nbrs_i$ ..... One-hop neighbors of i

$P_l^{\boldsymbol{BE}}$ .... The average bit error probability

P_i .... The total power dissipation

P_l^R .... The packet loss rate

P-R-D .... Power-Rate-Distortion model

P_{ri} .... Reception power consumption

$P_{r_{max}}$ ...... The maximum reception power

P_{sh} .... The encoding power at node h

P_{sh}^m .... The encoding power spent to compress one bit of data in level m

P_{ti} .... Transmission power consumption

$P_{t_{max}}$ ...... The maximum transmission power

q .... The network lifetime inverse

QoE ...... Quality of Experience

QoS ...... Quality of Service

R_h .... The data rate at node h

R_h^m .... The data rate at node h to be compressed at compression level m

$\mathcal{R}_l$ .... The link reliability

$\mathcal{S}$ .... The sink node

$\mathcal{S}(X)$ ...... The size of X in Mb

RREQ .... Route Request

SPD ...... Successive Perturbation Distribution

T .... Convergence threshold

TCC_{VS} .... The total number of clock cycles

T_{net} .... The network lifetime

UPD ...... Uniform Perturbation Distribution

$\mathcal{V}$ .... Set of video sensor nodes

V_{dd} .... The supply voltage

V_T .... The thermal voltage

WMSN . . . Wireless multimedia Sensor Network

WSN . . . . . Wireless Sensor Network

WVSN . . . . Wireless Video Sensor Network

x_{hl} . . . . The data rate, originated from node h, at link l

η_{hi} . . . . The flow conservation

γ . . . . The encoding efficiency coefficient

σ . . . . The variance of video encoder (in terms of MSE)

DEDICATION

** I dedicate my work to the one who gave me life, the symbol of tenderness, who sacrificed herself for my happiness and my success, to my mother.

** To my father, a school of my childhood, who has been my shadow during all the years of study, and who has ensured throughout my life to encourage me, to give me help and to protect me.

** To my adorable sisters Amina and Chahinez and my sweetheart niece Maria KALKOUL. To my dear brother Zakaria and my handsome brother Laid KALKOUL.

** To my loving, encouraging and supportive soul-mate Nazim YAZZA. I thank my god everyday for having you in my life.

No dedication can truly express the deep love I feel for you.

** To everyone I love. I dedicate this work.

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Introduction

General Introduction

Wireless Video Sensor Networks (WVSN) are today considered as a promising technology, notably because of the availability of miniaturized multimedia hardware (e.g., CMOS cameras). WVSNs embrace a large variety of applications in several domains (civilian as well as military areas), such as home automation, elderly person assistance, advanced health care services, real time tracking of objects, industrial quality process control, etc.

Unlike traditional wireless sensor network (WSN), wireless multimedia sensor networks capture rich multimedia content (video, images, etc.). WMSN stand for a collection of nodes, each of which able to capture multimedia data (video, images, audio) in addition to scalar measurements (temperature, humidity, etc.), to eventually process them and finally to deliver data/results through multi-hop communications to a central node, called sink. Upon receiving this data, the sink, by means of data fusion mechanisms and/or analysis techniques, delivers to upper layers (applications, end-user or cloud) relevant information.

Motivations

Designing and implementing WVSNs raise many research issues because precisely of the constraints they impose. In fact, in WVSNs, there are two contrasting requirements: higher video quality required at the sink for analysis purposes, leads to voluminous data which in turn consumes network resources and hence reduces its lifetime. Inversely, reducing data volume for lifetime preservation will lead to poor video quality at the sink.

Depending on the application requirements, some applications may require high visual quality in order to perform complex processing operations (e.g., face recognition) whereas other applications can accept lower visual quality (e.g., presence detection). Hence, the required visual quality at the sink can be expressed as an application parameter. On the other side, delivering high data rates (*i.e.* high visual quality) will draw down the resources of the network, in particular the energy of nodes, as the latter are driven by batteries. Thus, the desired quality of the multimedia content at the sink is often the major issue that impacts the application of such networks. Consequently, it is necessary to elaborate solutions in order to respect the desired video quality at the destination level whilst ensuring the maximization of the network lifetime.

Even though multimedia content can be compressed in order to minimize data rates, this latter remains voluminous for WVSNs resources. Indeed, the increase of compression level reduces the number of bits to be transmitted but at the same time increases the video distortion at the destination level and conversely. Hence, two main challenges should be considered: **a)** the processing of the multimedia content and **b)** the reliable routing of the latter. On the one hand, the encoding of the captured multimedia data depends highly on the desired quality. Thus, finding a balance between the visual quality at the sink and the video encoding (i.e., the compression level) at the source nodes is a crucial task. On the other hand, the reliable delivery (i.e., the chosen routing protocol) of the video content can highly influence the network's lifetime.

In fine, processing and delivering multimedia content are not independent tasks, and their interaction has a major impact on the network lifetime.

Main Contributions of this dissertation

Motivated by how to prolong the network lifetime as longer as possible in a distributed manner, while taking into account the limited resources of the video nodes, the main contributions in this thesis concentrate on designing a novel approaches that overcome the previously mentioned problems and that efficiently respond to the application requirements. The main contributions of this work can be summarized as follows:

1. First, we concentrate our interest on the first challenge, namely, the processing of the multimedia content, in which the main challenge is to find a balance between the encoding power and the resultant bits size at the source node, while ensuring the desired video quality at the destination level. Thus, the research question that was targeting within this contribution is: *How the network can find, in a distributed manner, such a trade-off between the desirable visual quality at the sink and the available network's resources in order to prolong the network lifetime as longer as possible?*

   To answer the aforementioned question, we propose a **fully distributed approach** that is able to derive the optimal encoding power and source rate at each video node in a way to meet the network constraints (limited link's bandwidth) on one hand and to prolong the network lifetime on the other hand. The choice of a distributed approach is primarily motivated by: (a) the scalability of distributed approaches overs centralized ones and (b) the non-reliability of wireless sensor networks in general and WVSN in particular which makes distributed approaches more appropriate than centralized ones.

   To overcome the limitations of literature approaches, we propose a novel approach that is able to find the optimal encoding power and source rates allocations which maximizes the network lifetime independently of any networks settings.

   We conduct an in-depth simulation analysis of the proposed approach providing a deep analysis about the impact of the optimization on the network lifetime. We also analyze and discuss the impact of the stopping criterion.

2. After ensuring an optimal power/rate resource allocation that maximizes the network lifetime while respecting the desired video quality at the destination, we extend our proposal by allowing it to handle a **dynamic change of links capacity**. This extension allows facing: (a) the data loss (b) and the low network connectivity. In other terms, we include additional constraints. To this end, a novel mathematical model is formulated considering both limited links capacity and limited transmission and reception powers. In order to compare the proposed solution over state-of-the-art

approaches, we implement, in addition to the proposed approach, the one, named DQLM [49] as the most representative approach, using OMNET++ simulator. Simulation results show that our approach increases the network lifetime by 4 times compared to DQLM solution, which demonstrates the efficiency of our proposal. Furthermore, we extend the proposed approach to handle channel transmission errors, and a retransmission mechanism, based on the two-state Markov Chain [46], is used to cope with this issue.

3. Then, in order to tackle the second challenge, namely, the reliable delivery of the multimedia content. First, we study the routing protocols proposed in WMSNs. From the literature, several approaches have been proposed to deal with routing in WMSNs. Nevertheless, the routing has been treated as a separate issue without considering the energy consumption at each node for data encoding. On the other hand, the power-rate-distortion solutions have focused only on how to find and ensure an optimum power-rate resource allocation, while assuming a pre-defined routing matrix. Thus, in this contribution, the research question that is targeted is: *How can a routing protocol affect the network lifetime, and how to choose an appropriate routing to maximize the network lifetime?*. Consequently, we analyze the behavior of various routing protocols implemented as an add on to the fully distributed algorithm of the first contribution. The analysis is conducted on two different configurations, and we compare convergence delays, network lifetime improvement and battery consumption of these different routing algorithms. The results confirm our claim, depicted in the fact that the network lifetime maximization does not depend only on power-rate-distortion optimization, but also on the chosen routing protocol across the network by optimally selecting the forwarding candidate.

4. After that, and before starting the combination process of the two axes, namely, the data processing and data routing axes, we prove that the problem of choosing a single routing protocol among n routing protocols is NP-complete. Then, we start the combination process that can be summarized as follows:

- Initially, we start by integrating the routing issue into the analytic model proposed in the first contribution, that ensures a trade-off between the desirable visual quality at the sink and the available network's resources. Based on different criteria and on an unknown routing matrix, a solution is proposed that optimally selects the forwarding nodes, based on the shortest path solution. The resolution of the novel optimization problem is semi-distributed and provides one-path, two-paths or three-paths from the source nodes to the destination (the number of the required paths can be expressed as an application parameter). We conduct an in-depth simulation analysis of the proposed approaches over two main parameters: battery consumption and network lifetime. The simulation results first show that our proposed solution ensures the convergence of the system. Second, the latter consumes less than 0.03% of the total battery and thus ensures a prolongation of the network lifetime between 7 to 12 times, depending on the considered topologies, in comparison to the baseline approach (i.e., without optimization).

  It should be noted that, in this part, even if the routing axis takes into account the topology of the network, and that the proposed analytical model considered both the data routing and data processing axes' constraints, the problem was divided into two sub problems, in which the resolution of the data processing axis cannot be achieved without the results of the data routing axis. Nevertheless, the resolution of the data routing axis problem (i.e., routing problem) did not consider any of the parameters of the first axis (data processing axis).

- Hence, we extend our study and propose a fully distributed solution that respects both the optimal resource allocation and the reliable end-to-end delivery of multimedia data content. In this part, and in order to maximize the network lifetime, the routing axis cannot be achieved without the data rate and links capacity parameters, determined and updated by the data processing axis. On the other hand, the data processing axis cannot be achieved without the routing tables updated by the routing axis. Thus, a novel analytical model is proposed with more constraints (using the data processing axis constraints of the second contribution). The proposed solution optimally selects the forwarding nodes based on both an energy-aware geographic forwarding and a link reliability. Our novel solution allows an end-to-end routing with local decisions at each video sensor node without end-to-end path discovery and maintenance. In other terms, our solution is completely distributed and hence, can cope with **dynamic change of network topology**. Furthermore, we propose a new dynamic path selection mechanism. The latter allows choosing the sufficient number of paths needed to ensure a reliable data transmission and traffic distribution. The number of paths selected should respect the optimal data rate generated at each video node and links capacity.

  In order to evaluate the performance of our solution, a simulation analysis of the proposed approach through two representative topologies is conducted. The simulation results show that the network lifetime is increased by 7.47 and 7.67 times for the first and second topologies, respectively, compared to baseline approach.

5. The expected extension of our works is to consider links' reliability; i.e., wireless links are error-prone in nature. Consequently, finding a solution that dynamically adapts to this kind of disruption is essential to guarantee the performance of data delivery. In this part, we concentrate on multimedia content delivery while taking into account the following: **(a)** the remaining energy of the intermediate nodes, **(b)** the optimization steps that allow an optimal resource allocation and **(c)** the sudden perturbation that can appear. Thus, we propose a fully distributed solution taking into account the dynamic change of link's reliability (implemented using probabilistic perturbations distribution). In the proposed solution, the link's capacity can be adjusted depending on the remaining energy of the forwarding nodes. The resolution of the optimization problem is fully distributed and can cope with dynamic topologies, in contrast to the approaches proposed in the literature. The proposed solution uses the multipath routing mechanism in order to balance the network load. The simulation results show that the proposed solution consumes less than 0.16%. Additionally, the proposed algorithm, of distributed nature, ensures a prolongation of the network lifetime by at least 5.14, 4.56 and 5.59 times for the successive, uniform and gaussian perturbations, respectively. In order to save more energy, we extend the proposed solution after the convergence of the system. In fact, once the optimization phase ends, only the data transmission will continue. In this stage, the incoming link's capacity of a given node will be decreased with respect to the remaining energy of the latter. The simulation results show that, with this solution we can save till 25% of the energy compared to the solution without considering the remaining energy of the intermediate nodes after the convergence of the system.

Organisation

The dissertation is organized as follows: chapter 1 presents an overview of the main concepts related to wireless video sensor networks such as: architecture, applications, main features and issues, as well as the two main aims and the objectives of this dissertation. Chapter 2 presents an overview of the network lifetime maximization approaches in wireless multimedia sensor networks. Chapter 3 presents the first contribution, in which a fully distributed algorithm is proposed to maximize the network lifetime by jointly optimizing the encoding power and the source rate while respecting the desired visual quality. Chapter 4 presents the second contribution of this thesis, that extends the first one by allowing it to handle a dynamic change of links capacity and includes additional constraints in the mathematical model, proposed in the first contribution, considering both limited links capacity and limited transmission and reception powers. In chapter 5 the third contribution is addressed, where the impact of several routing protocols on the network lifetime is proved. Chapter 6 presents the fourth contribution that addresses the combination process of the data processing and data routing axes in order to maximize the network lifetime. In chapter 7 we complete the combination process while considering a dynamic WVSNs taking into account the dynamic link's reliability and the dynamic link's capacity (that changes depending on the remaining energy of intermediate nodes). Chapter 8 gives a general conclusion about the whole work presented in this thesis.

I

Wireless Multimedia Sensor Networks: Generality and state of the art

1

Wireless Video Sensor Networks: Generality

1.1/ Introduction

Many real applications (wild, medicine, etc.) have driven the development of Wireless Sensor Networks (WSNs). These tiny devices, with low computational power and memory, have the ability to sense and to capture the relevant information from the environment in which they operate and to transmit them to the end user (the sink). The scalar sensor networks respond to several application requirements (temperature, humidity, etc.). However, other applications have more demanding needs (video surveillance, elderly person monitoring, etc.). In this respect, and to meet these expectations, a new generation of devices has emerged: communicating multimedia sensors giving rise to Wireless Multimedia Sensor Networks (WMSNs) targeting several real applications [60], [82], [81]. In fact, WMSN is a network of interconnected wireless sensors loaded with the appropriate modules (*i.e.*, microphones, camera) in order to retrieve video, image and audio data, as well as scalar data depending on the application requirements as shown in figure 1.1, in a context of a car. It has allowed the emergence of various application domains (such as: medical, military and even civil applications) and thus the evolution of the research domain. Consequently, the type of the used module (combined with the sensor node) determines the type of the used network, and thus, the emergence of plenty of sub-multimedia networks. For example, when only a camera module is used, we then talk about Wireless Video Sensor Networks (WVSNs).

Unlike traditional sensor networks, where data processing is mostly simple and even negligible in terms of energy consumption, in Wireless Video Sensor Networks (WMSNs) the captured data is usually voluminous and requires local processing before transmission. The rest of this dissertation focus on wireless video sensor networks. Figure 1.2 shows an example of a WVSNs composed of 11 video sensor nodes and one sink deployed in a monitored area.

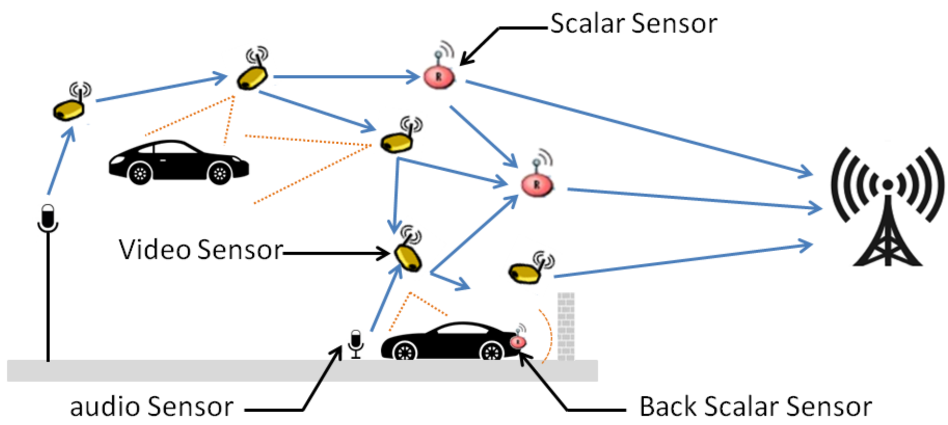

Fig. 1.1: Example of traffic control using WMSN.

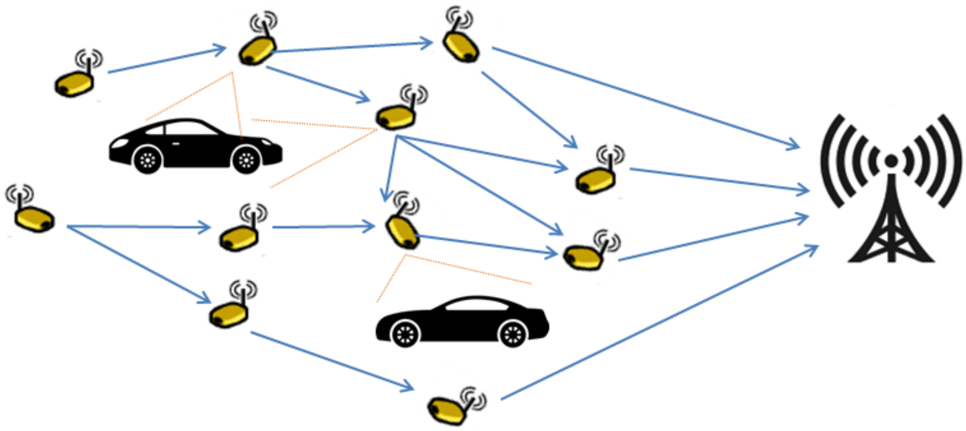

Fig. 1.2: Example of traffic control using WVSN.

1.2/ TERMINOLOGIES

Before going further, let us present the definition of the main terminologies to be used in this dissertation.

1.2.1/ VIDEO DISTORTION

The video distortion refers to the quality of the video at the destination. More is the distortion worst is the quality of the video. The distortion is calculated in term of Mean Square Error (MSE).

1.2.2/ ENCODING POWER

The encoding power refers to the consumed power required to compress the video data. More is the encoding power more is the level of the compression and thus more is the distortion at the final destination.

1.2.3/ Scalar sensors and scalar data

The scalar sensors (commonly called, the traditional sensors) are tiny devices that can transform the state of the observed physical quantity into a usable quantity. However, they can only detect and manipulate a simple data such as: temperature, pressure, flow measurement or physiological phenomenon (when they are placed on, in or around the human body). This kind of the collected data is also called scalar data. The processing of the scalar is mostly simple in terms of energy consumption.

Note that, in this dissertation we only use the wireless video sensors whose architecture is described in the following section.

1.3/ Video sensor node architecture

A video sensor node is a small electronic device that is able to perform several tasks, and it is composed of several modules. Each of which has a particular functioning, such as the collection of relevant environmental information, the processing and the communication of these latter. Thus, a video sensor node generally has four base components [2, 41, 50, 101] that can be defined as follows:

1.3.1/ The sensing unit

The sensing unit is the interface with the external environment. The main role of this unit can be divided into two sub-roles. The first role is to retrieve the video and scalar data from the physical environment. The second one is to convert the collected information using the Analog-Digital Converter (ADC) in order to be transmitted to the processing unit.

1.3.2/ The processing unit

The processing unit is particularly essential to video sensor nodes. Let us recall that, the multimedia content is usually voluminous and need to be compressed before transmission. This unit is the only responsible of this processing and the result of this treatment is stored in a memory. Another task of the processing unit is the execution of the code that defines the behavior of the video sensor node. Since a video sensor node operates under a battery constraint, the processing unit should have low power consumption, high speed calculation, and also should be small.

1.3.3/ The wireless communication unit

The wireless communication unit ensures the communication between the various nodes of the network via a radio communication medium. In traditional WSNs, this unit is considered as the most consuming unit in term of energy. However, in WMSNs the most consuming unit in term of energy depends on the application requirements. In fact, if higher video quality is required, which means a large number of bits should be transmitted, in this case, the wireless communication unit is the most energy consuming unit.

Otherwise, the processing unit is the most energy consuming unit. For wireless communication, there exist three common standards for radio frequency communication: Wi-Fi (IEEE 802.11 wireless LAN), Bluetooth and ZigBee (IEEE 802.15.4).

1.3.4/ The battery unit

Usually, the source power in wireless video sensor networks is a battery (with a limited lifetime). The latter has the responsibility of managing the node's energy over the aforementioned units (namely, the sensing unit, the processing unit and the communication unit) in order to ensure the expected tasks. Unfortunately, in some applications, this battery can not be recharged or replaced, and the drain of a given node energy can impact the whole network lifetime. Thus, in WVSNs, the energy, in particular, remains a very challenging task.

The aforementioned units are the most important units of a video sensor node. In addition to them, some nodes can handle additional units depending on the application requirements, such as:

- **Localization system:** it is a component included that can provide information about the geographic location, such as GPS (Global Position System).
- **Mobilizing System:** this component can be used in mobile video sensor networks, it allows the mobility of nodes, since in some application the nodes should move to fulfill the requested task.

Figure 1.3 shows an example of video sensor node architecture.

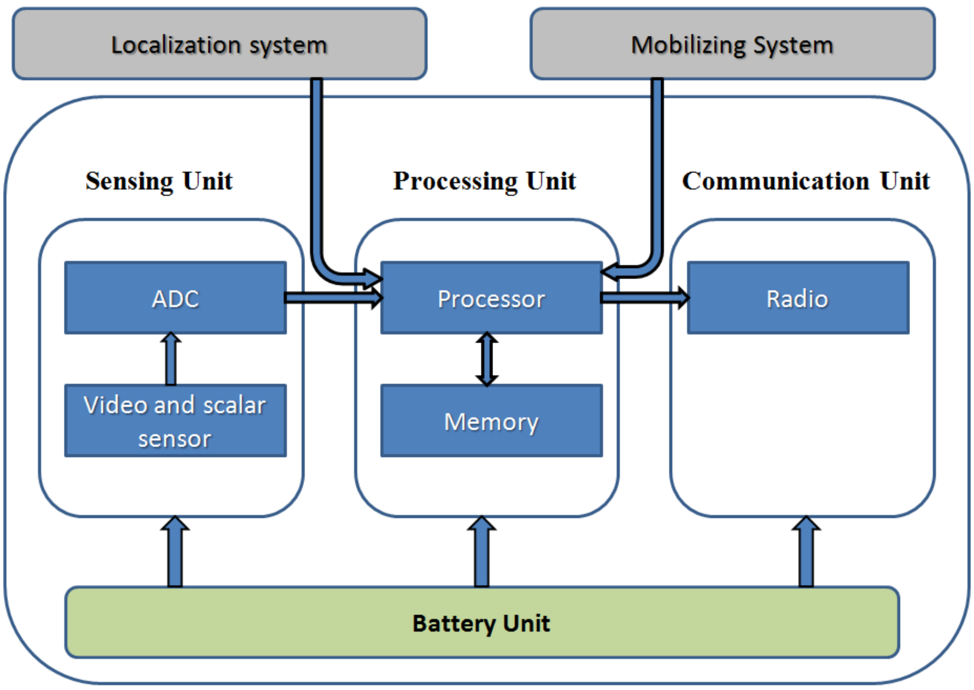

Fig. 1.3: Video sensor node architecture.

1.4/ Applications of WVSNs

As soon as they appear, wireless video sensor networks have attracted the interest of several application domains, given their tiny size, their symbolic cost and their efficiency. Examples of applications of wireless video sensor networks in different domains are described below:

1.4.1/ Multimedia surveillance sensor networks

Video sensor nodes can be used to enhance and complement the scalar sensor nodes in monitoring applications [42, 66]. In fact, the video nodes can identify and track objects from their visual information. Let us take the home security applications as an example. In this context, the traditional sensor nodes can be used for a gas leak detection, while the video sensor nodes can be used for outdoor home security, such as the detection of an unauthorised or unwanted person in the secured areas.

Note that, the video sensors are used not only for security monitoring, and can also have benefits from being used inside the house. One of the plenty existing examples is the parents that keep watching their kids while they are still at work [59, 81].

1.4.2/ Military Applications

In such a domain, the use of wireless video sensors is very useful and appreciable. These latter are able to detect a variety of events such as pressure, the presence or absence of certain type of objects (chemical, biological, or radiation agents), their position, speed, size, or even their direction.

Researchers in Libelium [74] have released new generation of autonomous 3G sensors equipped with video cameras that can be used in applications with night vision mode requirements (take pictures in total darkness) for a military application among other security applications.

1.4.3/ Assistance for the elderly persons

Statistics from World Population Prospects [1] show that the number of older persons will be doubled by 2050 and tripled by 2100, which mean that the number of older persons will reach the 2.1 billion by 2050 and 3.1 billion by 2100. Thus, developing a new technology that minimizes the need for caregivers and help elderly to survive an independent life is a crucial task.

The video sensors can be used for elderly behavior surveillance and detection of abnormal activity to take the necessary precaution and ensure that help reaches them quickly in the case of an emergency [92]. Moreover, families with senior parents can get peace of mind especially if the used video sensors enable a real time communication and have expression/emotion analysis (such as the Intel RealSense 3D sensor [127]) to detect if their parents are sad and determine if it is necessary to visit them.

1.4.4/ Advanced Healthcare

The use of wireless video sensor networks has also attracted the attention of the health care application. In fact, video sensors can be implanted in a person's body, and facilitate the diagnosis of a disease and monitor its progress, or even follow the reconstruction of a muscle.

In nowadays, the best method to measure the pain level of a patient is a famous 1 to 10 scale. However, this method is far from being precise. Thus, in Binghamton University the researchers have built a 3D Facial Expression Database [128] that combined with a camera can identify and quantify the pain states.

Moreover, Fujitsu [45] has developed new technologies based on video sensors that analysis the behaviour of a patient and can recognize a normal behavior (examples, sleeping, sitting) of an abnormal one (example, turning in a restless effort to get to sleep). The difference between an ordinary behavior and the one demanding attention is based on the magnitude and frequency of the patient's movements.

Note that, each time our heart beats, our head moves slightly. Thus, researchers in Computer Science and Artificial Intelligence Lab (MIT) are working on a new technology that translates those head movements into an accurate data on heart activity [57].

1.4.5/ Environmental monitoring

Traditional wireless sensor networks are widely used in the environmental field because of their capabilities to detect natural disasters (storm, flood, forest fire). The video sensor nodes can be used as a complement to these latter and give more relevant information such as the level of propagation of the fire, or real time view of the damage caused by storms.

Another important field of using video sensors in environmental monitoring is the oceanography applications. In fact, authors in [58] have used the video sensors to study the nearshore zone. The used video sensors are protected against the weather by waterproof housings and can measure the incoming waves and predict heights of waves and danger from currents.

1.4.6/ Traffic avoidance and control systems

To illustrate this point, smart parking [40] can be used as an example, among many others. In fact, recent statistics [63] show that, on average, people spend a total of **nine full days** per year looking for free parking spaces, especially in mega-cities which experience heavy traffic near malls, restaurants or shopping centres. This phenomenon is more pronounced in downtown areas, which lack the necessary space to build new parking. Car traffic is often synonymous with air pollution and noise, in addition to the "wasted" time experienced by drivers when they are looking/waiting for a parking box. To cope with such a problem, one can use *presence* sensors, buried in the ground such as *SENSIT* [91] (installed in Moscow, Boulevard Ring). However, the deployment of such systems requires costly roadway works. The usage of WVSNs could be an interesting alternative to such expensive systems, since they do not require costly deployments [11].

Real applications using video sensors were already implemented, in Boston for example they use cameras and inductive loops to manage traffic [31]. Recently, in Metz city in France, a few number of video sensors were deployed in order to secure pedestrian crossings [23]. In fact, when a large number of pedestrians arrive at the crossroads, the green times may not be sufficient to allow everyone to cross safely. Thus, this new technology allows adapting the crossing time depending on the number of the pedestrians.

1.5/ Data management in WVSN

Wireless video sensor energy problem has caught lots of researchers attention in recent years. The main reason is that Wireless Video sensor Network (WVSN) can provide both scalar and visual information of the monitored area, and thus, much more details and precision for target monitoring. However, the voluminous of the multimedia content combined with the limited resources of video sensor nodes makes the proposed solutions in traditional sensor networks, where the collected and processing of data is usually negligible, inapplicable in WVSN.

Thus, before reaching the destination node, the multimedia content must follow several steps [7, 70, 72, 97] as described below:

1.5.1/ Data gathering

Each video sensor network operates differently and depends on the end user requirements. Thus, there are three types of data gathering: **a)** event detection, **b)** full-time detection and **c)** on-demand detection or even the combination of these latter.

- In the event detection category [85], a video sensor node only sends its data when significant events are detected depending on the application requirements. In WVSNs, the event detection is commonly used for tasks such as fire detection, and the main goal here is to provide high-accuracy event detection while saving the node's energy.

- The full-time streaming [97] is the most consuming data gathering in term of energy. In fact, the video sensors keep detecting and transmitting the video content of the monitored area such as track moving objects. Note that, the video sensor needs to compress (in real time) its collected data before each transmission and thus can rapidly drain its energy.

- For the on-demand detection [103], the data transmission is initiated by the destination node (namely, the sink node) by sending a request, to get specific type of data, to the video nodes of the network. The nodes with the requested data or in the area of the requested data collect and send back these latter on the inverse path. The temporary detection (*i.e.*, on-demand detection) in WVSNs is commonly used for tasks such as examine a team's work in order to reduce assembly time.

1.5.2/ Data Compression

Energy conservation is a critical issue in WVSNs since video sensor nodes are powered by battery. As multimedia content is usually voluminous, encode (*i.e.*, compress) the latter, pre transmission, becomes an inescapable task in order to reduce transmission overhead, and hence, extended the network lifetime. However, the main research challenge for video compression is to find the appropriate algorithms that are suitable for limited video nodes resources.

Firstly, the video is converted into frames (group of sequential images). Then, the video compression algorithm can be applied.

In fact, in WVSNs, two different kind of compression are usually used, the inter-frame coding and the intra-frame coding. In intra frame coding (*i.e.*, spatial compression), the compression is done within one single frame at time without taking into account what frame comes before or latter (*i.e.*, does not take into account the temporal changes). In contrast, inter-frame coding (also called temporal compression) is a type of compression that takes into account other frames, in other words, it looks into the future frames and tries to identify (determine) what is changing and saving the difference in each frame.

The inter frame compression is more suitable in case of small memory. However, it requires more energy for data processing and can results in a less video quality at the destination level. Conversely, the intra-frame compression requires less processing energy and ensures better video quality. However, it results in a large file size.

Thus, in order to balance the two types of compression, the hybrid compression can be used. figure 1.4 shows the frames of a video. The frames can be categorized into three types: I-frame (intra-coded), P-frame (predicted) and B-frame (bidirectional). The I-frames are the frame with most important information and can be compressed using the intra-frame compression (I-frame priority is always much higher than P-frame and B-frame). The P-frame and B-frame have less important information, and thus, can be compressed using the inter-frame compression.

Among the hybrid CODECS (Compressior/Decompressior) used in wireless video sensor network, we cite: H.264/AVC [105, 118] encoder and MPEG-4 [43] encoder.

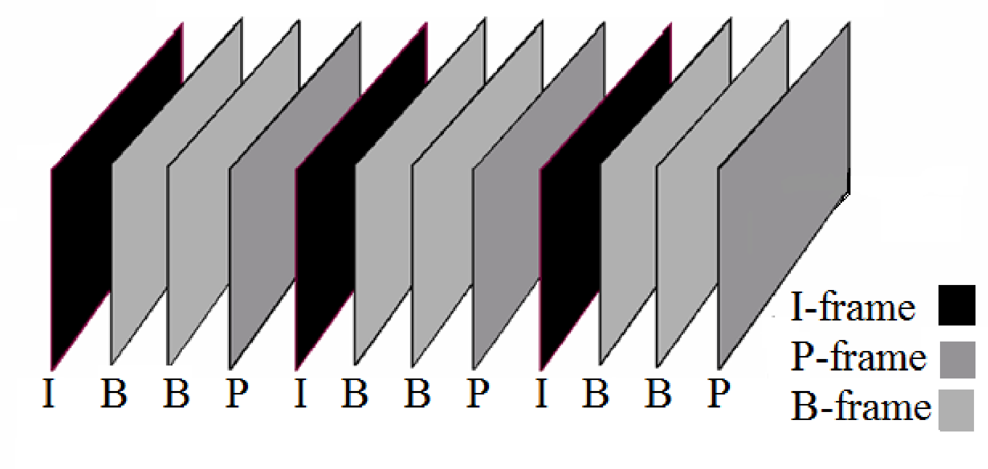

Fig. 1.4: Converted video into frames.

The encoded video is then transferred to the destination node (the sink node), that will decode the data to extract the video. The latter is usually a resource-sufficient device.

1.5.3/ Data transmission

Note that, even with the video encoding (*i.e.*, compression), the video content is still much voluminous compared to the scalar data used in traditional WSNs. Thus, routing algorithms designed for WSNs can not be directly applied for video applications that require high-bandwidth, high processing energy and specific QoS requirements. Consequently, the high-efficiency video routing has become an important research focus in WVSNs.

Note that, depending on the architecture of the WVSN, the routing can be classified as flat routing and hierarchical routing. In flat video sensor network architectures, all nodes are identical and have the same level. In other words, these latter have the same functions, the same capabilities, and must operate together in order to manage the network and accomplish the desired tasks. Thus, the nodes can directly communicate the collected data to the base station (*i.e.*, the sink) if the latter is in their communication range. Otherwise, a multi-hop communication will be used through the intermediate nodes. The base station will then handle the transmission of data to the processing center.

In hierarchical networks, some nodes have more energy and/or more computational power. Thus, different tasks can be assigned to different nodes of the same network. The main characteristic of such a network is the nodes division into several groups of nodes called clusters. Based on different criterions (such as, the quality of the communication, the power, the communication range, etc.), the node representing the cluster is chosen (usually called the cluster head (CH)). The latter is responsible for managing its cluster, such as aggregating the data collected by the nodes of its cluster, as well as the transmission of these data to the base station. Additionally, the communication between the nodes can be done directly only if the two communicating nodes are part of the same cluster. Otherwise, a request should be reported to the cluster head.

Figure 1.5 shows the difference between the architecture of the two networks.

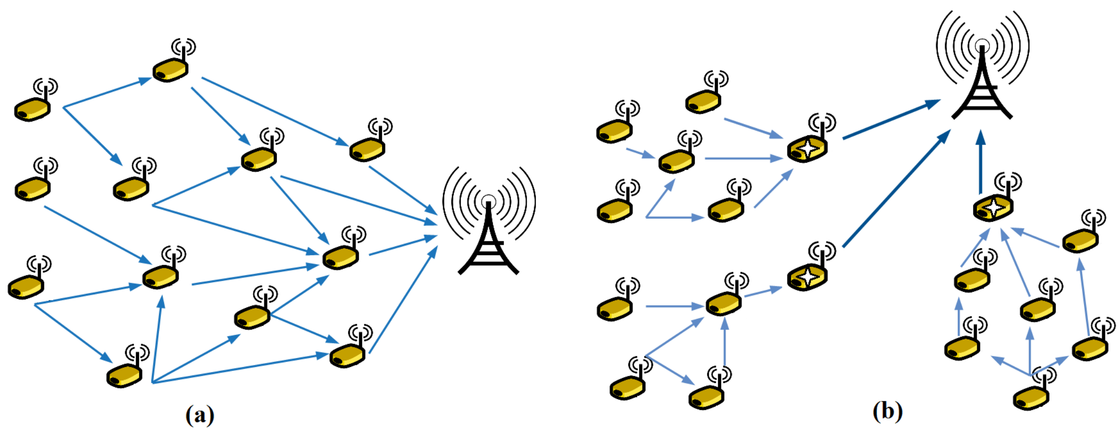

Fig. 1.5: (a) Flat network, (b)Hierarchical network

Additionally two types of routing can be used in order to transmit data to the sink node: the single path routing or multi path routing. Since, the multimedia data are voluminous, the multipath routing seems to be the most suitable routing in WVSNs. The multipath routing approach has the potential to enable low power consumption and high data-rate transmission. This approach can be used either to split the data over the existing paths, and this to balance the network load over the different nodes of the network, or to duplicate data across these latter, and the main objective here is to ensure a high reliability.

1.6/ Challenges in WVSNs

There are several main peculiarities that make WVSNs challenges differ from their predecessor (*i.e.*, WSN) challenges, which has driven researchers to develop new algorithms and protocols better suited to video sensor networks. Depending on the application requirements, each wireless video sensor network has a variety of challenges and constraints [6, 37, 111], which are detailed hereafter.

1.6.1/ Resource constraints

The tiny size of video nodes, as well as their minimal cost have imposed hard constraints for WVSNs in terms of energy, memory and computational capacity. In fact, as most applications rely on the use of wireless sensors, energy has been and still a primary constraint since the replacement of the batteries, once the latter exhausted, seems to be very difficult and even impossible in some cases. The latter has driven designers and researchers to consider the importance of conserving energy and integrating mechanisms that extend the node lifetime, and thus, the whole network lifetime.

Due to the huge data size in wireless video sensor networks, the memory constraint is a crucial task in such a network. The most traditional scalar sensor nodes are integrated by 1KB to 4MB memory [48], while memory space in video nodes can reach 2GB using the *Waspmote* video nodes [75]. However, it stills very small compared to the voluminous multimedia content. Thus, the collected data should be compressed before being stored.

The computation capabilities are another issue in wireless video sensor networks, and its directly related to the processing unit (*i.e.*, compression phase). Depending on the type of compression used (inter-frame, intra-frame or hybrid compression), it is more complex for the processor to encode the temporal frames (relative to other frame in the video sequence) then the spatial frames (not relative to any other frames in the video sequence). Thus, finding a trade-off between the two compression types is fundamental in order to, not only preserve the desired video quality at the destination level, but also to minimize as much as possible the encoding complexity and hence the encoding power.

1.6.2/ Channel capacity

To transmit data from the source node to the sink node, video sensor nodes use a multi-hop communication, and the data are transmitted via wireless medium. However, the wireless medium used in such a network is limited and dynamic (*i.e.*, differs from one link to another). The dynamic change of links capacity depends on the interference perceived at the receiver, as well as the reception power of the latter. Thus, the source rate generated at each video node and transmitted through wireless outgoing links should respect the capacity of the these latter.

1.6.3/ Multimedia processing

Since the video sensor nodes operate under battery constraint, the captured data needs to be compressed before transmission. However, some applications may require high visual quality in order to perform complex processing operations (*e.g.*, face recognition) whereas other applications can accept lower visual quality (*e.g.*, presence detection). Hence, the required video processing can be expressed as an application parameter. Note that, more is the compression level (and thus the energy used to encode data) less are the data to be transmitted and hence, more is the distortion at the destination level. On the other side, less is the compression level, higher are the data to be transmitted and hence more is energy consumed for data communication. Thus, the main challenge here, is to find a **trade-off** between the compression level at the source node and the desired video quality at the destination level.

1.6.4/ Multimedia coverage

Constructing a video sensor coverage (VSC) is an efficient way for a panoply of applications (such as, tracking and the surveillance military camp, airport and prisons) since they can provide more detailed information (*i.e.*, real vision) of the region of interest. At the difference with traditional sensor networks where the sensor node has an omni-angle of sensing range represented by a disc, the video sensors may have a limited angle of sensing range represented by an Angle of View(AoV). Due to this difference, the coverage algorithm for traditional sensor networks can not be directly applied in this special class of networks.

Based on the literature [5] [26] [115], the coverage problem can be seen from three different angles, namely, target coverage, area coverage and barrier coverage. **Target coverage** allows the coverage of one or more objects in a well-defined area without the need to monitor the whole area (*e.g.*, monitoring of a historic monument in an exhibition instead of the entry hall). While the **area coverage** refers to monitoring the whole considered area and any change within the later should be detected immediately (*e.g.*, Volcano area). Finally the **barrier coverage** where there is no need to cover the whole region, but only construct a line of sensor networks and thus to detect the crossing objects (*e.g.*, barrier deployment on the roadway to detect the wild animals crossing).

The main research challenge here is to identify the minimalist subset of video nodes (with crossing FoV), from the set of nodes deployed in the monitoring area, to be activated in order to detect any intrusion into the monitored area.

1.6.5/ Dynamic topology

The wireless video sensor network topology is unstable and changes frequently over time due to video sensor failure, such as energy depletion or physical destruction of a node. Other important factors are: the mobility of nodes, the insertion of new nodes, or even the links failure. In these cases, video nodes should be self-managing and reconfigure themselves in order to adapt to failures.

1.6.6/ Network lifetime

After a certain period of time, the power supply of a given node (usually a battery) will be exhausted. In most cases, the replacement of a battery is impossible especially in hostile environments (such as, Volcano area). Thus, depending on the target application and its context, several definitions of the network lifetime can be formulated. Let us consider a sensitive WVSN surveillance application where a nuclear center is surveyed. In such an application, any suspicious activity must be detected and reported as immediately as possible because of the security threats it represents. Therefore, the network lifetime here can be defined by the depletion of the first node energy. In another context, such as video surveillance of deer in their wild environment [55], the network lifetime can be defined by the depletion of the last node energy. However, among the main research challenges in wireless video sensor network, we find the network lifetime maximization problem.

1.6.7/ Scalability

The video sensor network can contain dozen, hundreds or even thousands of video nodes. During a failure of some sensor nodes, it should be possible to insert new nodes in the network while maintaining the performance and services provided by the latter.

1.6.8/ Robustness and fault-tolerance

The collected multimedia data are derived from natural images. Therefore, can not be classified in a limited data size. On the contrary, they are sensitive to the conditions in which they were taken, especially the weather conditions (snowy weather, heavy rains, autumn leaves, fog, etc.) or even urban elements such as the presence of an obstructing truck of a part of FoV, or attacks. These conditions, which are not ideal for use, can be seen as perturbations of ideal video data. Thus, the algorithms that process these data must be robust to these perturbations/attacks [15, 131].

In addition, the decision algorithms must incorporate the possibility of hardware failures, *i.e.*, physical. For example, some sensors may become partially defective and some transmissions may temporarily be disturbed [86]. Thus, the algorithms must be tolerant to a set of identified failures [130]: instead of stopping to work, these algorithms should have to continue to work in these degraded modes to provide even partial but relevant information.

1.6.9/ Security requirement

Many applications of wireless video sensor networks collect sensitive information. However, the WVSN characteristics such as, multi-hop communication and wireless medium expose information to multiple types of security and privacy attacks (*i.e.*, eavesdropping, modification, loss, injection), and make the possibility of these attacks more likely to appear than in the traditional wireless sensor networks.

Unfortunately, the existing security mechanisms such as asymmetric cryptography used in wireless networks cannot be directly brought to WVSNs given the limitations in terms of power budget, memory capacity, communication and computational abilities of video sensors. Additionally, the security mechanisms applied for scalar data in WSN can not be efficiently brought to WVSN. Thus, to establish a trust relationship among the WVSN sensors and to ensure a secure forwarding of collected data from the video nodes to a collection point, a new algorithms and security mechanisms must be implemented.

1.7/ Wireless video sensor network design

One of the most difficulties that can be encountered in WVSN, is the design of this latter. Due to the hard and limited resources of the used tiny devices, in terms of energy, memory, communication and computational abilities, the design problem becomes more and ore challenging. Mathematical models, such as the optimization methods, have shown a great potential to represent the system, while taking into account its characteristics, its limitations and thus respecting the way it operates.

In this section we briefly introduce the optimization problem formulation. The first step towards the formulation of an optimization problem is, first of all, the identification of the objective(s) allowing the realization of the system. Such an objective can be, in the case of video sensor networks, the maximization of the network lifetime, the minimization of the distortion, the minimization of the paths to be chosen, etc. The definition of such an objective can be expressed by an objective function, that one seeks to optimize (minimize or maximize), with respect to the variables/functions influencing the latter, called constraints. The constraints can be expressed by an inequality (*i.e.*, $C_1(x) \geq 0$) and/or an equality ($C_2(x) = 0$).

Thus, the optimization problem has, in general, the following formulation:

$$\begin{aligned} \text{minimize} \quad & f(x) \\ \text{subject to} \quad & C_1(x) \geq 0, \\ & C_2(x) = 0, \\ & x \leq x_{max}, \end{aligned} \tag{1.1}$$

where $f(x)$ presents the objective function to be minimized, x presents the function parameter, $C_1(x)$ and $C_2(x)$ the constraints and x_{max} presents the domain constraint.

Note that, such a formulation is far from being easy to achieve, since the simpler the model is, the less it represents the practical system. On the other side, the more complex is the model, the more difficult is to solve this latter.

Once the optimization problem is formulated, there is a panoply of algorithms allowing its resolution. However, the choice of the resolution algorithm strongly depends on the optimization problem. Thus, the choice of such an algorithm is crucial and can even determine the success or the failure of the resolution.

1.8/ Aim and Objectives

Unlike scalar data, multimedia data can be collected at different resolutions [97], on which depends the content quality (*i.e.*, video quality neatness). In other words, the higher is the desired quality, the better is the perception of the content and the bigger is the data size. Therefore, the latter requires higher processing and storage capacities of the video sensors [56]. The first obstructing point here, from a scientific research point of view, is to reconcile these orthogonal constraints while satisfying the objective of the target application.

Thus, the algorithms to propose can act on several parameters to control the system. Firstly, on the multimedia data processing parameters, namely, the compression level of the collected data and the resultant transmission rate. Secondly, on the multimedia data transmission parameters, namely, the links reliability and the intermediate nodes energy, in other terms, the adequate routing protocol. These parameters will have a direct impact on the quality of the data delivered to the end user.

The choice of the values of these parameters can not be fixed once and for all, but must, on the contrary, remain dynamic. To do this, it seems judicious to propose a distributed optimization method determining the values of these parameters dynamically according to the environmental changes. The programmable devices of the system (video sensors) will have thus to determine by themselves the values of these parameters according to their close environment.

The main objective of this work is to maximize the network lifetime while in a distributed manner. Thus, two axes have to be considered: data processing and their routing given their considerable need in terms of energy consumption.

1.8.1/ Data processing axis

In the data processing axis, the main problem lies on the transmission of the multimedia data that must be compressed before being transmitted. However, less is the compression level, more are the data to be transmitted and more is the energy consumed to ensure the transmission. In this case, the communication unit is the most consuming unit in term of energy. On the other side, more is the level of compression, less are the data to be transmitted and more is the distortion of the video at the destination level (degradation of the quality). In this case, the processing unit is the most consuming unit in term of energy.

Thus, in this axis, the main parameters to consider are the encoding power (*i.e.*, the compression level) and the size of the resulting bits. While the main challenge is to find a *trade-off* between the encoding power at the source node and the desired video quality at the destination level.

1.8.2/ Data routing axis

Even though video content can be compressed in order to minimize data rates, it remains voluminous compared to the scalar data retrieved in traditional sensor networks. Thus, new strategies should be employed to balance network load and consequently balance the energy consumption of the video nodes.

The main challenging task, in this axis, is to dynamically select the best forwarding nodes, and thus, constructing an end-to-end routing with local decisions at each video sensor node without end-to-end path discovery and maintenance (*i.e.*, cope with **dynamic**

change of network topology). To do so, it is fundamental to consider the data rates resulted from the data processing axis in order to determine the number of paths required to ensure the transmission and hence the visual quality at the end user level.

The energy of the intermediate nodes that are near to the sink node is another concern, since these latter use energy at very high level because the traffic of incoming neighbors is also forwarded by these nodes. In addition, wireless links are error-prone and unreliable in nature. Consequently, finding a solution that dynamically adapts to this kind of perturbations is essential to guarantee the performance of data delivery.

Thus, for the data routing axis, the main parameter to consider is the path (or paths) to be chosen in order to transmit data from the source to the destination, in other words, what is the suitable routing protocol to maximize the network lifetime.

In fine, processing and delivering video content are not independent tasks, and their interaction has a major impact on the network lifetime.

In this work, we confine our interest on network lifetime maximization in a fully distributed manner while taking into account the two aforementioned axes, namely, data processing and data routing axes.

1.9/ CONCLUSION

The progress realized in the recent years in wireless video sensor networks demonstrates their effectiveness and thus considered as a technology of the future. The particular characteristics of the latter have been able to attract the attention of both the research and industrial communities. However, the hard constraints of the tiny video sensors make the design of such a network a first concern of the researchers trying to overcome these constraints, while ensuring the well functioning of the system.

This chapter has presented an overview of the main concepts related to wireless video sensor networks such as: architecture, applications, main features and issues, as well as the two main axes that should be considered in order to maximize the network lifetime, namely, **data processing** and **data routing** axes

Therefore, in the next chapter, we will present a theoretical state of the art focusing on distributed approaches that maximize the network lifetime while respecting the desired visual quality at the destination level.

2

State of the art

Treating videos has been the concern of researchers for a long time, starting by the traditional video communication applications (*i.e.*, such as digital TV broadcast, personal video recording), until wireless video sensor networks. However, the video processing differs from one network to another. If we take a look into the literature, in wireless adhoc networks for example, the first concern was mostly to route the high rate multimedia data and to ensure the video quality at the destination level without considering the multimedia processing power consumption [35, 61, 113, 124]. However, the researchers in wireless video sensor networks have to consider not only the limited video sensors resources, in terms of memory, transmission and reception powers, but also the high requirement in term of encoding power.

Thus, in this chapter, we examine the literature works where the main objective is to maximize the network lifetime in wireless video sensor networks while respecting the desired video quality at the destination level. For each of these works, we present the characteristics of the proposed strategies, which will allow us to position our own work in relation to the existing ones.

2.1/ Classification of solutions

Several approaches have been proposed in the literature to deal with the network lifetime maximization problem. However, this problem was addressed based on two separate fields: the data processing axis and the data routing axis. One one hand, the approaches proposed for the data processing axis focus only on how to find and ensure an optimal trade-off between the available resources at the source and the desired video quality at the destination level, while assuming a predefined routing matrix. On the other hand, the approaches proposed for the routing axis treat the latter as a separate field. In this case, the energy consumption spent by each node for data encoding was not considered. Thus, the proposed solutions in the literature can be broadly classified into two categories: data processing approaches and data routing approaches.

2.1.1/ Data processing approaches

In the data processing approaches the main parameters to be considered are the encoding power (*i.e.*, the power consumed during the data compression) and the resultant data size (*i.e.*, the data to be sent after the compression phase), since more is the encoding power, less are the data to be transmitted, and hence more is the distortion of the video at the destination level. Additionally, the encoding power has a major impact on network lifetime. For this, the solutions proposed in this category take into account the latter while maintaining the desired video quality at the sink node. It should be noted that in this category, there are solutions based on the formulation of an optimization problem (2.1.1.1) and others not (2.1.1.2).

2.1.1.1/ Optimization problem formulation approaches

Starting by the solutions that are based on the optimization problem formulation, of which we quote:

He et al [54]- (2009) Based on the Power-rate-Distortion(P-R-D) model, He et al [54], proposed a fully decentralized solution to maximize the network lifetime in WMSN with a unicast routing, while assuming an existing standard MAC protocol to deal with link scheduling. A mathematical model, that jointly considered the source rates, the encoding powers, and the data delivery distortion, was developed and solved in a fully distributed manner through the Lagrangian duality and Subgradient method. A large spectrum of simulations was done considering also the transmission errors in both large and small delay applications to quantify the impacts on the maximum network lifetime. However, the proposed model did not ensure the convergence at any initial configuration which might lead to problems with no feasible solution.

Gürses et al [49]- (2009) Through another P-R-D model, proposed in [77], authors in [49] proposed a distributed quality-lifetime maximization solution in WMSN, where they integrated the distortion model in the objective function instead of considering it as a constraint. The problem was formulated based on Generalized Network Utility Maximization (GNUM) [87], and solved by using the *Proximal Point Algorithm* [19]. However, the Lagrangian formula is separable only over power consumption and rate allocation, while to update the Lagrangian multipliers, each node required the inverse lifetime, which is computed in a centralized manner by the sink and sent back to sources. Thus, in addition to the fact that the latter is semidistributed, this solution might lead to a large delay, additional power consumption and even could lead to network congestion.

Tahir et al [114]- (2009) In the same context (*i.e.*, maximizing the network lifetime), authors in [114] have proposed a solution to find the optimal tradeoff between communication and computation power consumption. An optimization problem was formulated taking into account the delay as a quality of service constraint. The problem was solved in a distributed manner using a dual decomposition (*i.e.*, divided into two sub-problems). However, the transmission and reception energy costs, as well as the packet length and the capacity of each link were fixed, which cannot be practical in real wireless video sensor applications. In addition to that the distortion was not treated.

Zou, Junni and Tan [134]- (2010) In [134] the authors have proposed a solution that jointly optimizes the network coding based multi-path routing, the network flow control as well as the encoding bit rate. A fully distributed algorithm was presented and solved through the Lagrangian and Subgradient method.

Zou, Junni and Xiong [135]- (2011) In similar work, joint source/channel coding was proposed in [135]. An appropriate trade-off between the minimum data distortion and maximum network lifetime was studied and formulated as an objective function. The problem was formulated by introducing the power consumption for each of: (a) error control, (b) data communication, (c) video encoding and (d) network coding. The proposed solution was solved in a distributed manner by primal decomposition. However, the definition of the source encoding rate can lead to no feasible solution with respect to the source encoding distortion caused by the video compression.

The network coding used in problem formulation in both [134] and [135], aims to reduce delays and increase network lifetime over data aggregation at the intermediate nodes. However, this method needs to decode and encode the transmitted data at the intermediate nodes resulting in an additional power consumption. Additionally, the destination node needs to be completely synchronized with the transmitting nodes, and the capacity of the wireless medium was set to a fixed value.

Sarif et al [104]- (2012) A heuristic power and rate allocation solution was proposed in [104], in which the video encoding parameter was determined based on the location of nodes in the network with respect to the sink. The network was divided into zones, on which is based the obtaining of the source rate and encoding power parameters to achieve the required distortion. However, this solution is centralized and depends on the number of zones.

El-Sherif et al [39]- (2013) Another optimum power and rate allocation solution was described in [39]. To communicate with the sink, each sensor node uses the TDMA as a medium access control to avoid collision and ensure that the video quality is not affected by the wireless medium. However, this solution requires all nodes to be synchronized. However, only single hop mode was considered which implies that nodes should be as close as possible to the sink. Additionally, this proposed solution is centralized and did not consider at all the power consumption during data reception.

You, Lei, et al [129]- (2013) In [129], authors have addressed the problem of resource allocation in rechargeable battery context (*i.e.*, energy harvesting). The problem was formulated as an optimization problem where the objective function aims to minimize the distortion of visual content for all sensors while considering the total energy dissipation at each node. However, the distortion was calculated based only on the source rate. The encoding power was further calculated, *i.e.*, once the source rate is determined: there is no tradeoff between the two parameters. Finally, only a single hop communication was considered, and the resource allocation problem was solved at the sink level.

Arar et al [12]- (2017) The problem formulated in [12] takes into account, not only the processing distortion (*i.e.*, P-R-D [56]) but also the channel distortion model. The objective function aims to minimize the energy consumption of each node in the network that combines both static video nodes and cluster heads (*i.e.*, hierarchical network). Then, the problem was solved using the proximal minimization algorithm [19]. However, authors did not consider the reception power at the cluster head while formulating the objective function. Moreover, they used the one-hop or multi-hop mechanism, since if the multi-hop mechanism is used the flow conservation at each video or cluster head should be considered. In addition to that, the proposed solution is centralised, and the capacity of each link was fixed.

Nguyen, Thanh-Hieu, et al [90, 121]- (2017) In the same context of network lifetime maximization, authors in [90, 121], have proposed a solution that is based on a hierarchical deployment. In addition to the camera sensors (CSs) and cluster heads (CHs), authors have defined another type of sensor called supernode (SN) with the most powerful energy. The optimization problem was formulated over two sup-problems. The first problem tackles the time switching optimization in which the SN chooses the cluster that has the maximum energy in order to capture the video demanded by the sink node. The second problem tackles the optimal rate allocation under limited bandwidth, which also defined by the SN and sent to cluster head of the chosen cluster. The CSs are responsible for the capture and the pectization of the demanded video. However, the encoding and reception powers were not considered, and the proposed solution is not distributed.

2.1.1.2/ Non-Optimization problem formulation approaches

He, Wu [56]- (2006) In order to optimize the resource performance under the video sensor nodes resource constraints, authors in [56] have proposed a resource allocation and performance analysis of wireless video sensors under two scenarios, small and large delay requirements. The main objective in [56] is to develop an analytic power-rate-distortion (P-R-D) model to highlight the relationship between the video encoder and its rate distortion performance. The latter was widely used to estimate the power of the video compression.

Nguyen, Thanh-Hieu, et al [32]- (2012) Authors in [32] have proposed a novel clustered architecture for WVSN, in which both the source node and the end user are resources constrained (e.g., video surveillance applications where remote users can have portable/mobile devices for real-time monitoring). A gateway was introduced and it is responsible for matching the complexity requirements of both ends. In order to minimize as much as possible the energy consumed for data compression at the source node, motion estimation function have been moved from the encoder to the decoder (namely, a wired powered gateway). The gateway also matches the output rate to the bandwidth constraints of the outgoing transmission channel and takes into account the type of the end-user terminal. However, the aforementioned parameter (*i.e.*, data rate) is determined in a centralized manner. Additionally, moving the motion estimation to the decoder can effectively reduce the energy consumed during the data compression, however, it results in a huge volume of data transmission and hence enormously impact the network lifetime.

Alaoui-Fdili, et al [10]- (2014) Using the H.264/AVC encoder, authors in [10] have proposed a novel model that enables to predict the energy consumed during the video compression of any H.264/AVC encoder. The latter aims to minimize the energy consumption while taking into account only intra-coding mode. However, the video distortion at the destination level was not studied.

Aruna, N., et al [13]- (2015) Different from the aforementioned solutions, authors in [13] have proposed a compressed sensing based quantization with prediction encoding for video transmission. The solution focuses mainly on reducing the data to be transmitted based on a technique called compressed sensing (CS) after a block spars. Then an algorithm for the data recovery was proposed, and the distortion at the destination was studied. However, the energy consumed either during the compression level, or during the data communication was not taken into account, and the routing was not addressed.

Nandhini, et al [88]- (2015) In order to minimize the energy consumption, authors in [88] have focused on minimizing the complexity of the encoder and thus to minimize the encoding power. To this end, a video compressed sensing (VCS) framework based on the discrete wavelet transform (DWT)-discrete cosine transform (DCT) hybrid approaches was implemented using two matrices. Even thought, the energy consumed during the matrices generation was considered, however, the energy needed for the data compression was not addressed. Additionally, the reception power was not considered, which can lead to erroneous results, especially if the multi hop communication is used as it was claimed in [88].

Ahmed, Adel A [3]- (2016) Authors in [3] have proposed a low power encoding mechanism based on H.264 encoder that was considered as a suitable encoder for a limited bandwidth network transmission such as the WMSNs. The complexity of such an encoder was discussed and developed. The total consumed energy was formulated based on the encoding energy consumption and transmission energy consumption. However, the energy consumed during data reception was not taken into account, and the routing was not discussed at all.

Kim, Yong-Min, et al [69]- (2017) In the same context, authors in [69] have proposed a compression scheme in order to minimize the energy consumed during data transmission. To do so, the area to be monitored was divided into dynamic area and static area. Considering these characteristics, the proposed scheme only extracts and compresses the dynamic area in an efficient manner. The distortion was addressed based on the bit-plane deletion (*e.g.*, when a significant bit plane is deleted, the original data is highly damaged), and the amount of the transmitted data were significantly reduced. However, the energy consumed during data compression was not addressed.

Yang, Hong, et al [126]- (2017) The main objective presented in [126] is to preserve the video quality at the destination level. To do so a scalable key frames (KFs) scheme and scalable winer-ziv frames (WZFs) scheme were proposed for different channel bandwidths in the context of wireless video sensor networks. However, the solution was proposed without considering neither the transmission and reception powers, nor the energy consumed during data compression, which is a crucial task in such a domain.

Alaoui-Fdili, Othmane, et al [9]- (2018) Unlike the aforementioned research, authors in [9] have proposed a solution that dynamically chooses the encoding level and the resultant frame rate depending on the given distortion and the remaining energy of the concerned source node. This solution takes into account the Intra-only H.264/AVC encoder. However, the energy consumed during data reception and the dynamic link's capacity were not considered.

2.1.2/ Data routing approaches

After the advent of computers and their increasing power, the need of communication has led researchers, in the twenty-first century, to a new wireless technology: the Internet, which has attracted growing interest. The popularization of this technology has made it possible to evolve the means of communication, particularly with the emergence of Ad Hoc networks characterized by their heterogeneity and their lack of infrastructure.

Routing in wireless ad hoc networks is an important feature that allows to follow the information from the source to the destination in a wireless network. Thereupon, the first routing protocols for wireless networks have begun to emerge. Therefore, and before going further, we will briefly introduce some of the well-known routing protocols in ad hoc networks.

Dynamic Destination-Sequenced Distance-Vector (DSDV) [53] DSDV is a proactive protocol based on the Bellman–Ford algorithm. In order to select a route, DSDV uses an updating table with the following information: the destination, the next hop, the number of hops and the sequence number. The updating of the sequence number was the main contribution in DSDV and used to avoid the routing loop problem.

Dynamic Source Routing (DSR) [65] DSR is a dynamic routing protocol that uses two phases in order to define its routes. Firstly, the source node triggers the routing discovery phase by sending a route request message (RREQ) to all its neighboring nodes with the corespondent message identifier. These latter insert their address to the RREQ and broadcast the message until reaching the destination. At the reception of the message the destination replies by sending the route reply (RREP) message via the inverse route. Thus, only the source node has to maintain the routes. In order to maintain the routes, the source node executes the second phase, which is the path maintenance. When a node i detects a fatal transmission problem, a route error (RERR) message is sent to the source of the packet, that will remove the node i from the saved path. Subsequently, a new route discovery operation is initiated.

Ad-Hoc On-Demand Distance Vector (AODV) [95] AODV is a reactive protocol and is essentially an improvement of the DSDV algorithm and uses the two phases of DSR. Thus, it follows the following steps: the path establishment is on demand, by using the RREQ and RREP of DSR. In order to avoid the transmission errors the RERR is also used. Then, the next hop, the number of hops and the sequence number of the DSDV are used to cope with the routing loop problem. In addition to the aforementioned messages, the AODV uses HELLO control packets that allow to verify the connectivity of the links.

Optimized Link State Routing (OLSR) [29] OLSR is a proactive protocol that selects the optimal paths based on the shortest routing in term of the number of hops to the destination. The discovery of the neighbors is done by the sending of the Hello message while the control of the connectivity is done by sending a Topology Control (TC) message. In order to decrease as much as possible the network traffic, each node selects a set of nodes called multipoint relays (MPR) allowing to reach until Two-hop neighbors. The MPR nodes are responsible of sending the TC messages as well as the traffic routing.

The scientific community has shown great interest in studying the routing in ad hoc wireless networks in recent years. Traditional Wireless Sensor Networks (WSNs), Wireless Multimedia Sensor Networks (WMSN) or Wireless Video Sensor Networks (WVSN) are some of these ad hoc networks dedicated to a particular application. However, these latter are known by their resources limitation. Thus, the routing protocols proposed in ad hoc network can not be brought efficiently in WMSNs in general, which was proven through simulation results of multiple literature works [30, 78]. Therefore, in the following, we will be interested in the proposed routing protocols for WVSN.

In addition to scalar data, the WVSN should ensure the transmission of multimedia content, including snapshots (*i.e.*, images) and multimedia transfer. As a result, reliable routing (*i.e.*, the chosen routing protocol) of the video content can strongly impact the network lifetime. For this, the work presented below was based primarily on the optimization of routing to maximize the lifetime of the network.

2.1.2.1/ Optimization problem formulation approaches

Madan et al [79]- (2006) In order to maximize the network lifetime in traditional sensor networks, authors in [79] have focused on the problem of computing the optimal traffic flow. The problem was formulated as a linear programming problem, and the sub-gradient algorithms are used to solve the latter in a distributed manner. However, authors in this paper have considered a fixed value for the transmission rates on each link.

Shu, Lei, et al [110]- (2008) Different from the aforementioned research, the main focus in [110] is to achieve a desired network lifetime that was considered as input. To do so, two main parameters were considered, the dynamic transmission radius through which the maximum data source can be determined, and the minimum delay that was reinterpreted as the maximum transmission radius. Then, a routing protocol was proposed while ensuring a node-disjoint routing path and guarantee that the routing paths will be found if they exist. However, the data processing, prior to the transmission, and the distortion level was not treated.

Zhang, Lin, et al [132]- (2008) and Shu, Lei, et al [109]- (2010) In order to transmit the multimedia content from the source to the destination, authors in [109, 132] have proposed a multi-priority multi-path selection (MPMPS) scheme, in which the stream with the higher priority is sent through the more suitable paths, whilst the other streams can use the paths with the longer end-to-end transmission delay. However, the rate generated by the video sensor as well as the sensor maximum transmission capacity were fixed. Additionally, the data processing and the distortion were not addressed.

Melodia, Tommaso, and Ian F. Akyildiz [83]- (2010) At the same context, authors in [83] have proposed an optimization problem formulation that takes the minimization of the average energy, required to successfully transmit a payload, as an objective function. The main QoS requirements are the packet error rate, the rate control and the delay control. In order to choose the best downstream node, the source node starts by broadcasting a *CONTRACT-REQUEST* with the required QoS (*i.e.*, the maximum end-to-end delay, the required bandwidth and the allowed end-to-end packet error rate). However, the energy consumed during data processing and the distortion were not considered.

Lin, Kai, et al [76]- (2011) Different from the aforementioned researches work, authors in [76] have proposed an hierarchical based solution. The network consists of a set of multimedia source nodes divided in several clusters. Each cluster is monitored by an agent node that was considered as not limited by energy. The main research focus is to select one routing with high energy efficiency and service of quality. To solve this problem, authors have leveraged social networks to select the most trustable node in term of quality of service (QoS). Then, each sensor node selects its forwarding nodes based on the trust node, its remaining energy as well as the correlation parameter. However, the transmission power, the reception power, the data fusion power as well as the capacity of the links were fixed. Moreover, the energy consumed during data processing and the distortion were not treated.

Razzaque et al [100]- (2011) By exploiting the geographic locations and QoS performance of the neighbor nodes, authors in [100] have implemented a localized hop-by-hop routing. Moreover, the protocol (almost) ensures a homogeneous energy dissipation rate for all routing nodes in the network through a multi-objective Lexicographic Optimization-based geographic forwarding. The problem was formulated using the multi-objective Lexicographic Optimization (LO) approach. Moreover, LO exploits only local information to make routing decisions. The absence of a global routing scheme reduces the networks setup and updating costs. However, the proposed solution deal with a fixed transmission power, reception power and link's capacity. Additionally, the distortion was not treated, and the processing power was not included.

Shah, G. A. et al [107]- (2012) In order to enhance the performances of the network, authors in [107] have proposed a solution that maximizes the number of the sources while taking into account the distortion level at the destination node. The data were transmitted using a multipath routing protocol that ensures and maintains three disjoint paths from the source node to the destination node. The source rate generated after the compression level dynamically changes depending on the available bandwidth, and the reliability of each link was defined in term of end-to-end tolerable packet loss rate. However, the computed distortion is only based on the transmission and decoding errors, while the distortion caused by the compression process as well as the energy consumed during this phase were not taken into account. In addition to that the energy consumed during data transmission and reception were ignored.

Dai, R. et al [34]- (2012) The problem of correlation aware QoS routing was studied in [34]. In fact, to prevent network congestion, a correlation-aware load balancing was proposed based on splitting the correlated flows to different paths. Then, an optimization problem was formulated with the sensor's energy minimization as an objective function, subject to delay and reliability constrains. The original idea behind this paper is that the nodes with overlapped field of view (FoV) merge their data to ensure more compressed data. However, it results in more dependency among frames. In addition to that, a centralized processing step was introduced, in which the sink node should calculate the overlapped ration of FoVs between all the nodes of the network and broadcast the results. Furthermore, even if the energy consumed during data processing was formulated, only the energy consumed during data transmission was considered in the optimization problem (*i.e.*, during the intermediate node choosing). The data rate was fixed, and the distortion was not considered.

Xu, Hongli, et al [125]- (2012) The main research focus in [125] is to minimize the power consumption subject to achieving a sufficient bandwidth while exploiting the benefits of node-disjoint multi-path routing. The links relaying the source to the destination were assigned by the bandwidth weights, and each intermediate node can act as cooperative or non-cooperative relay node. Then two solutions were proposed (*i.e.*, centralized and distributed). However, only the transmission power was considered, the source rate was fixed and the distortion level was not studied.

Guan, Zhangyu et al [47]- (2013) In the same context, authors in [47] have proposed a solution that is based on the cooperative relay nodes. The optimization problem was formulated to maximize the video quality at the destination level by jointly control the encoding rate, relay selection and the power consumed to transmit such a data. The encoding distortion as well as the packet loss distortion were considered, however, only the transmission power was considered (*i.e.*, the reception power and the encoding power were not handled).

Shen, Hang, et al [108]- (2014) In order to achieve the requirements QoS in WMSNs, authors in [108] have proposed a solution that leverages differential encoding to reduce redundant multimedia traffic as in [34] (*i.e.*, by exploiting the overlapped FoVs). Then, to achieve energy efficient delivery of video data, a selective approach of forwarding nodes was applied based on opportunistic routing. Finally, a multi-sink aware was considered. In this paper, the encoding power was considered in order to choose the nodes that should initiate the data transmission. However, the latter was not considered neither in the objective function that aims to minimize the energy consumption, nor during the performance evaluation, where only the communication energy consumption was studied. In addition to that, the source rate was fixed and the distortion was not addressed.

Magaia, Naércio, et al [80]- (2015) In [80], authors have proposed a new multi-objective approach for the WMSN routing problem. The Expected Transmission Count (ETX) and delay are used as QoS parameters in order to produce a diverse set of optimal solutions. The selection of the first path from source to destination (called initial population) is implemented with a Breadth First Search(BFS) algorithm. Since the execution time of the latter depends on the number of nodes, authors have used a crossover and mutation genetic operators to find the feasible intermediate sensor nodes. However the energy which has been consumed at each node during routes discovery have not been considered which affects directly the network lifetime. In addition to that, only one source-destination pair was considered, and the distortion was not studied.

Kim, H. W., et al [67, 68]- (2016) The proposed algorithm in [67] and [68] assumed that a set of video sensor nodes are woken up only during a short period of times (data transmission period). The event-driven data were delivered through active-mode nodes while trying to avoid the sleeping nodes whenever possible. Then, it selected a set of paths, that join every active node to the sink. However, the optimization problem does not consider neither the reception power consumption, nor the encoding power that have a direct impact on network lifetime. Additionally, the routing and channel allocation information were monitored by the sink (*i.e.*, in a **centralized** manner), and must be updated at nodes which intrinsically limits its applicability (*i.e.*, weaknesses of the centralized approaches within large distributed sensor networks). Furthermore, the latter results in additional power consumption for transmission and reception of such an information. Additionally, the distortion was not considered.

Hasan, et al [52]- (2017) Authors in [52], have proposed a novel path selection protocol that takes into account: **a)** the link quality, **b)** the disjoint paths selection, **c)** the power consumption and **d)** the end-to-end delay constraint. Each of the aforementioned constraints was presented by a mathematical model based on the Lagrangian Relaxation method. However, authors assume a fixed data length, which is not the case in practice with WVSN systems. Additionally, the encoding power required during data processing phase and the energy of the intermediate nodes were not taken into account.

2.1.2.2/ Non-Optimization problem formulation approaches

Park et al [94]- (2005) Authors in [94] have shown that the problem of routing messages in a wireless sensor network so as to maximize network lifetime is NP-hard. As a consequence, they propose a heuristic solution. The latter is based on delaying as much as possible the depletion of a sensors' energy to a level below that needed to transmit to its closest neighbor. However, the proposed solution is centralized, the transmission rate on each link is fixed and only payload transmission power was considered. Whereas, the encoding power, the reception power and the distortion were not considered.

Cobo et al [30]- (2010) Based on the hierarchical structure of the network, Bi et al. [30] have proposed an ant-colony optimization-based load balancing routing algorithm for WMSNs. In order to meet various QoS requirements (namely delay, packet-loss, energy and memory), authors only address the routing scheme between the cluster heads and the sink. To reach the sink, paths over the multi-hop communication are selected with respect to the aforementioned QoS metrics on each path. However, control packets used in this solution for route discovery cause a high overhead. Each sensor node indeed periodically broadcasts a HELLO packet in addition to the forwarding ants that have to reach the sink and go back for route discovery. Additionally, the data rate was fixed, and the encoding power was not handled.

Rosário, Denis, et al [36, 102]- (2012) To address this problem, a smart Multi-hop hierarchical routing protocol for Efficient VIdeo communication (MEVI) [36,102] have been proposed. Composed by both scalar nodes (denoted as non-CHs) and camera nodes (denoted as CHs). In MEVI solution, the scalar nodes select the CHs based on the Link Quality Indicator (LQI), and transmit their data using a single-hop communication. Then, the CHs finds a route (to transmit the received data) to the base station using two types of messages for route discovery (*i.e.*, route request and route reply). The base station can also send a multimedia content request to the CH, that will turn its FoV to the desired location and transmits the video content to the base station (BS). However, the encoding, the reception and the transmission powers were not discussed. Only one path is used to transmit the multimedia content which is a hard to realize process. Additionally, a failure of one CH may cause the network to lose a part of its tracking area.

Mohammadi, R., et al [84]- (2015) In order to enhance reliability, authors in [84] have proposed a multipath routing protocol based on the network coding mechanism. Firstly. a route discovery was achieved using a hello message. Then, a suitable next hop node was determined using a cost equation. Afterward, a source node coded its packets and transmits the latter to its next hop neighboring nodes. However, the transmission, the reception and the encoding powers were ignored. The distortion was not addressed and the data rate was set to a fixed value.

Hamid, Z., et al [51]- (2016) Different from the aforementioned clustering-based routing protocols, Delay and Link Utilization Aware Routing Protocol [51] was proposed for WMSNs. Three metrics were considered in routing decision: packet service time, channel utilization and remaining energy while taking into account a playout deadline. The proposed protocol selects the forwarding nodes by enabling the communication between the network and the MAC layers. However, if a source node requires a path to the destination, it starts by sending a RREQ to its neighboring nodes that will: a) update their routing information, b) replay to the source node, c) rebroadcast the RREQ to their neighboring nodes. This process continues until reaching the sink node, which can lead to a network congestion if several nodes request a path at the same time. The latter was confirmed by simulation results in terms of average throughput and end-to-end delay, that shows that more is the number of nodes, less is the performance of this protocol compared to previous protocols. Additionally, the data rate was fixed, the transmission power and the reception power were not discussed. Moreover, the encoding power, as well as the distortion were not considered.

Chen et al [25]- (2016) In [25], authors addressed the mesh topology, in which the E-Mesh route information collector and E-Mesh route selection should be maintained at each node. Based on the E-mesh route information collector, that contains the remaining energy, current load, and node position, the E-mesh route selection calculates the utility function. This latter evaluates the general condition of all nodes to select the most appropriate path while taking into account the least energy consumption, the optimal traffic load and the distance between the intermediate nodes. However, the transmission and the reception powers were not discussed, and the encoding power was not taken into account.

El, Mohamed et al [38]- (2016) Authors in [38] addressed the routing problem in wireless video sensor networks. The multimedia content was divided in four principal frames I-frame, P-frame, B-frame and data-frame. Depending on this division, an adaptive priority queuing was modeled, where the highest priority packets (*i.e.*, I-frame) are queued in buffer $Q1$, while the least priority packets (*i.e.*, P-frame, B-frame and data-frame) are queued in buffer $Q2$. The priority packets are sent first based on the path score function, which takes into account the network energy status, the available buffer, the number of hops and the number of lost packets. However, the authors did not consider energy consumed during the data processing phase. Additionally, this solution is semi-distributed, since the nodes received the calculated global score of the path(s) from the sink node.

Zonouz et al [133]- (2016) Authors in [133] have proposed a solution to enhance energetic efficiency during the routing process in traditional wireless sensor networks. In fact, the proposed solution combines both battery-powered sensor nodes and energy-harvesting sensor nodes, they used the residual energy of the intermediate nodes as a metric in order to establish the next hops nodes. However, the cost of the Energy-harvesting sensor nodes is relatively higher than a typical sensor nodes because of energy harvester devices [112]. Additionally, this solution discusses only a one path selection and used a uniform data generator for all sensor nodes which is not realistic in wireless multimedia sensor networks. The energy cost of such a solution was not discussed. Furthermore, the reception power, the encoding power as well as the distortion were not considered.

Aswale, S., et al [14]- (2017) At the same context, authors in [14] try to efficiently choose a path from the source to the destination by efficiently select the next forwarding node. The parameters that were considered are the link quality (referred to the link reliability of each link), the remaining energy and the distance between the next downstream node and the destination (the sink node). However, the capacity of each link was fixed but not used, and the data rate was fixed. Additionally, the encoding power and the distortion were not addressed.

Putra, E. H.,, et al [98]- (2017) Authors in [98] have proposed an energy-efficient routing based on dynamic programming. To find a route from the source to the destination, the proposed solution starts the path discovery from the destination to the source based on the weighted links (distance), and on the energy of the intermediate nodes. However, the energy formula was not discussed, the data rate and the video quality at the destination were not studied.

Ahmed, Adel A [4]- (2017) in order to transmit the multimedia content, authors in [4] have proposed a solution that mainly tackles the energy management and real time management problems while controlling the rate of the traffic sent to the network. In order to select the next hop node, three parameters were considered, the end-to-end delay, the received signal strength and the remaining energy of the intermediate node. In order to avoid the interferences, if an intermediate node receives two packets of different priorities it sends tho two packets, and then sends a feed-back packet to the node of the less priority packet in order to select a different path. However, the encoding power was not considered.

Usman et al [117]- (2018) In order to efficiently transmit the data from the source node to the destination while preserving the desired video quality, authors in [117] have proposed a framework for QoS and QoE for video transmission over wireless multimedia sensor networks. The solution takes into account a multi-path routing and the selected relay nodes is based on the available bandwidth of these latter. In order to transmit the encoded data, a source node will firstly send a data transfer request to its nearest neighbor, if the latter rejected the request more than three times, the sender node selects another relay node. However, this paper focuses mainly on how to efficiently compress the multimedia content and how to route this latter, as well as the distortion at the destination level, without considering neither the transmission and reception powers, nor the energy consumed during data compression.

2.1.3/ Data Routing *Versus* data processing approaches

To the best of our knowledge, the only works that have considered both the dat routing axis and data processing axis (especially the encoding power during the data processing) were presented in [8, 73] and will be summarized in the following.

Li, Chenglin, et al [73]- (2011) Authors in [73] have proposed a solution that joints the encoding and the routing in wireless visual sensor networks with multiple sink nodes. The problem was addressed by formulating an optimization problem that has both a network lifetime maximization and distortion minimization as an objective function. A large number of constraints was considered and decomposed in order to solve the optimization problem. Regarding the routing, the authors have opted for the multipath routing protocol with the shortest paths while respecting the capacity of each link. However, the two axes were treated separately. In other terms, the path discovery will be firstly solved in order to select the optimal two paths (that will be maintained). Then, the data processing will start in order to find a solution for power, rate and distortion control for a given subgraph. Additionally, the latter used the network coding that requires the decoding and the encoding of the data at the intermediate nodes and thus requires more energy consumption. Furthermore, the uniform deployment of sensor video was considered and thus cannot be brought efficiently to other monitoring applications.

Alaoui-Fdili et al [8]- (2018) Authors in [8] have proposed a novel approach that considers both encoding and transmission phases in a decentralized manner. The data encoding phase parameters (namely, frame rate FR, quantization parameter QP and FSP) were defined based on prediction models for an intra-only H.264/AVC based video encoder. Then the routing process started based on remaining energy and the reliability (predicted reliability) of each of the relying nodes. However, the two phases (*i.e.*, encoding and transmission phases) were treated separately, the energy consumed during data reception and the capacity of each link were not handled.

In order to compare the previously reviewed solutions, table 2.1 and table 2.2 depict the different parameters used at each solution. Note that, table 2.1 depicts the proposed solutions (from the literature) for **both** data processing and data routing axes that **used** an optimization problem formulation. While table 2.2 depicts the proposed solutions (from the literature) for also the data processing and data routing axes, but that **did not use** an optimization problem formulation.

The idea behind this classification (*i.e.*, in table 2.1 and table 2.2) is to highlight which of the parameters are mostly used in data processing approaches and ignored by the data routing approaches, and inversely.

Table 2.1: Optimization problem formulation solutions

			Data processing approaches								data routing approaches								
	papers		[54]	[49]	[114]	[134] [135]	[39] [12]	[104]	[129]	[90] [121]	[79]	[110]	[132] [109] [125]	[83] [68] [67]	[76]	[107]	[34] [108] [80] [52]	[47]	[73]
Optimization Problem formulation	Data processing parameters	Encoding power	x	x	x	x	x	x	x										x
		Dynamic source rate	x	x	x	x	x	x	x	x	x	x		x		x		x	x
		Static source rate											x		x		x		
		Distortion	x	x		x	x	x	x	x								x	x
		pre-defined routing matrix	x	x	x	x	x	x											
		Fully Distributed Solution	x		x	x					x	x	x	x	x	x	x	x	x
	Data routing parameters	Unknown routing matrix									x	x	x	x	x	x	x	x	x
		Dynamic link's capacity												x		x		x	
		Static link's capacity		x	x	x	x			x	x		x		x			x	x
		Dynamic link's reliability															x		
		Static link's reliability													x	x			
		Intermediate node's energy													x	x			
		Multipath routing	x	x	x		x				x	x	x	x		x	x	x	x
	Processing/Routing																		x

Table 2.2: Non-optimization problem formulation solutions

Non-Optimization Problem formulation	papers		Data processing approaches								data routing approaches											
			[56]	[32]	[10]	[88] [3]	[69]	[126]	[9]	[13]	[94]	[30]	[36] [102]	[51]	[84] [98]	[25]	[38]	[133]	[14]	[4]	[117]	[8]
	Data processing parameters	Encoding power	x	x	x	x			x													x
		Dynamic source rate	x	x	x	x	x	x	x	x										x	x	x
		Static source rate									x	x	x	x	x	x	x	x	x			
		Distortion	x	x		x	x	x	x	x		x				x	x			x	x	x
		pre-defined routing matrix	x																			
		Fully Distributed Solution										x		x				x	x	x	x	x
	Data routing parameters	Unknown routing matrix									x	x	x	x	x	x	x	x	x	x	x	x
		Dynamic link's capacity						x														
		Static link's capacity																	x	x		
		Dynamic link's reliability											x									
		Static link's reliability															x	x	x			x
		Intermediate node's energy							x			x	x	x	x	x			x	x		x
		Multipath routing	x	x			x				x	x			x				x	x	x	x
	Processing/Routing																					x

2.2/ Discussions and synthesis on the existing works

According to the bibliographical study based on the main works cited above, we can observe that the main research focus is to minimize the energy consumption in WMSNs and this to maximize the network lifetime as much as possible. We note particularly that the works treats the latter (*i.e.*, the network lifetime maximization problem) differently. Since the network lifetime maximization can be divided into two main fields, namely, the data processing and data routing, authors in the literature have proposed solutions that mainly focus on one axis (with its main parameters) without considering the other one. Thus, we present in the following a synthesis of: firstly the main parameters of the two axes and how they were considered by the proposed solutions in the literature. Then, we will focus on the general differences between the single-axis solutions. Finally, we present the general differences between the two axis approaches (*i.e.*, data processing and data routing axes).

2.2.1/ Data processing and data routing axes parameters

Let us firstly start by the data processing and data routing axes parameters borrowed from table 2.2 and 2.1.

Encoding power: the encoding power was mainly treated by the works that consider the data processing axis. The latter can be defined as the energy consumed during the data compression. Additionally, it should be considered into the total energy consumption formulation (with the energy consumed during data communication) in order to minimize the energy consumption, and thus, to maximize the network lifetime. However, the encoding power was not addressed into most cases that consider only the data routing axis.

The encoding power was presented in different ways in the literature. Next, we summarize the most used formulations. Note that table 2.3 presents the terminologies for all the variables used in the encoding power formulations.

- Firstly, the encoding power P_{sh} can be calculated based on the existing formulations from the literature, such as the P-R-D model proposed in [56]:

$$P_{sh} = \left(\frac{\ln(\sigma^2) - \ln(D_h)}{\gamma * R_h}\right)^{\frac{3}{2}}. \tag{2.1}$$

- Based on another P-R-D model [77], the encoding power can be computed as follows:

$$P_{sh} = \left(\frac{\log(\eta_s) - \log(D_h) - d_1 R_h}{\kappa_s}\right). \tag{2.2}$$

  We can observe that, the two aforementioned formulations, used in [54] and [49], respectively, have considered both, the data rate and the distortion parameters in the encoding power formulation. Therefore, we will opt for such a formulation that will be detailed in the next chapter.

- Secondly, from the literature we can observe that, the encoding power was formulated depending on the researchers requirements. For each solution was developed

Table 2.3: Terminology for encoding power formulations

Symbol	Description	Units
P_{sh}	The encoding power at node h	Watt
R_h	The data rate at node h	Mbps
D_h	The distortion at node h	MSE
P^m_{sh}	The encoding power spent to compress one bit of data in level m	Watt
R^m_h	The data rate at node h to be compressed at compression level m	Mbps
σ^2	The variance of video encoder (in terms of MSE)	MSE
γ	The encoding efficiency coefficient	$\mathrm{W}^{3/2}.\mathrm{Mb}^{-1}.\mathrm{s}^{-1}$
η_s, d_1, κ_s,	Constants	/
N_{cyc}	The number of clock cycles	/
C_{total}	The average capacitance switched per cycle	/
V_{dd}	The supply voltage	volt
I_0	The leakage current	Milliamps (mA)
f	The clock speed	/
V_T	The thermal voltage	volt
n	A processor dependent constant	/
TCC_{VS}	The total number of clock cycles	/

the suitable encoding formulation that best adapts to their expectations, we mainly cite:

$$P_{sh} = \sum_{m \in \mathcal{M}} P^m_{sh} R^m_h. \tag{2.3}$$

$$P_{sh} = N_{cyc} C_{total} V_{dd}^2 + V_{dd}(I_0 \exp^{V_{dd}/nV_T}) \left(\frac{N_{cyc}}{f}\right). \tag{2.4}$$

$$P_{sh} = 24.\left(\frac{TCC_{VS}}{100}\right) \tag{2.5}$$

As it can be observed from the formulations cited above, and used in [62], [9], and [3], respectively, the encoding power was formulated based on an estimation of the microprocessor load during the execution of the encoding scheme. Thus, the distortion was not considered during the formulation process.

Generated source rate: the generated source rate is usually related to the compression level of the multimedia data and thus to the encoding power, since more is the compression level (*i.e.*, the encoding power) less are the data to be sent and inversely. Thus, the latter is usually dynamic depending on the compression level of each sensor node. We can observe that, the latter is almost time dynamic in the works considering the data processing axis, while in the data routing axis it is usually fixed, and even if there exist works where the latter is considered as a dynamic one (in the data routing axis), it was not explained how.

Distortion: the distortion introduced by compression can heavily bias the results, and thus possibly leading to wrong interpretations. In traditional sensor network, the distortion is mainly related to the data rate. However, in WMSN, the latter should also take into account the encoding power, since more is the encoding power less are the data to be transmitted and hence more is the distortion at the destination level. Therefore, finding a balance between the encoding power and the resultant data size is a crucial task in order to not only save a node lifetime but also to respect the video quality required by the end user. From the literature, this trade-off is mainly addressed in the works belonging into the data processing axis, while in the few works that consider the distortion and belonging into the data routing axis, the latter was addressed taking into account only the generated data rate.

Routing matrix: As it can be observed from the literature, the routing matrix was usually considered as an input into the data processing axis works. The latter can hugely affect the results especially if the aim is the network lifetime maximization, since choosing the shortest path consumes much less communication energy compared to choosing the longest path (taking into account the intermediate nodes).

Distributed *Versus* centralized solutions: a centralized solution can be developed for the applications with few nodes deployment and in which the sink ensures the well functioning of the whole network. However, more is the number of nodes more is complicated to ensure the management of the network. Additionally, if the information (decision variables) coming from the sink node does not reach the nodes correctly, the system will not work properly. In contrast, the distributed solutions can be developed and beneficial for both large and small networks, since in the latter each node takes its own decision locally depending only on its one hop neighboring information and the nodes are self-organizing which is more suitable for dynamic networks.

Links capacity: since the data are transmitted via a wireless medium, one link can not ensure the transmission of the voluminous multimedia content considering its capacity. From the literature we can observe that the latter was fixed in the data processing axis works, which is not realistic since the latter depends on the reception power and the noise on each link.

Link reliability: the link reliability can be defined by the success of transmitting and receiving the sent packets in order to recover the original data. However, the reliability of each link is normally dynamic, especially in a wireless context due to the link failure, the obstacles, etc. From the literature, the latter is not usually addressed in WMSN, and how should the network behave if a sudden change occurs was not considered.

It was also observed, from the literature, that the link reliability can be addressed differently and can be categorized into three categories:

- **Link reliability at the network layer:** The most common link reliability estimation is the percentage of the received data at the destination or at the intermediate nodes. The latter is formulated as the ratio of the successfully received packets by the destination (the sink node or the intermediate node) to the number of packets generated and transmitted by source node [120].

- **Link reliability transport layer:** The second link reliability category takes into account the available queuing at the intermediate node. In fact, the available buffer size at the intermediate node informs the source nodes about the chances that the packets coming from the latter can be successfully buffered at the intermediate node, independently of the success or not of the transmission [8].

  Another way to address the link reliability, is to consider the total number of transmissions required for the source node to send all of the packets in its current window, and the number of successfully transmitted packets of the same window. Thus, the ratio of the two latter determines the success probability of the link for this window (the reliability dynamically changes whenever the window content changes) [100].

- **Link reliability at the MAC Layer:** The last one takes into account the state of the channel, where the channel states changes from a good state to the bad state and inversely depending on the propagation environment, transmission modulation and detection techniques implemented at the receiver [52].

Intermediate node's energy: from the literature, we can observe that the intermediate nodes energy was not largely addressed, which can lead to results drastically different from realistic ones. In fact, the multi-hop communication is the most widely used in WMSN due to the limited communication range of the sensor nodes. Thus, in order to prolong the network lifetime, it is necessary to take into account the energy of the intermediate nodes, not only during the path discovery phase but also during the data routing phase. Here again, the distributed solution can show its benefit. Consequently, when a node drains its energy under a certain threshold, it can simply notify the changes to its incoming neighbors that will either reduce their transmitted data to the latter or choose another intermediate node (s), instead of informing the sink node that will recalculate the paths and introducing more delay.

Multipath routing: as it can be observed, the multipath routing is the most used routing protocol in WMSNs. In fact, the latter can be used either to split the voluminous multimedia content through the existing paths, in order to gain in delay and divide the node's burden over the existing intermediate nodes (which is the most used technique), or to duplicate the data over the existing paths and in this case the main objective is to increase the reliability.

2.2.2/ Optimization formulation *Versus* non-Optimization formulation solutions in the data processing axis:

The difference between the optimization and non-optimization methods in the data processing axis can be highlighted as follows: in the optimization problem formulation, the main objective is to determine the authorized encoding power for the data compression process, without entering into the details (*i.e.*, the compression steps), and the resultant data rate in order to respect the distortion level. Besides, most of the optimization problem formulation approaches (either distributed or centralized) take into account the information of their neighborhood (a one-hop or more) to determine these parameters (*i.e.*, encoding power, data rate). In other words, the determination of these parameters is influenced by the information received from the neighboring nodes.

In contrast, the solutions proposed without taking into account the optimization steps focus mainly on the manner in which the collected data, by the video nodes, must be compressed in order to minimize the energy consumed by the encoding and thus deducing the frame rate, while respecting (or minimizing) the distortion at the destination level. On the other hand, these solutions did not take into account neither the distribution of the solution (since the proposed solutions focus on calculations that are only made and concentrated at the source node level), nor the parameters of the neighboring nodes that can affect the accuracy of these solutions (e.g. if the source node determines the rate to be sent after the compression phase, **but** the neighboring node can not support the transmission or even the storage of this latter).

2.2.3/ Optimization formulation *Versus* Non-Optimization formulation solutions in the data Routing axis:

In the data routing axis, we can observe that the most of the proposed solutions aim to minimize the energy consumption in the network by mainly minimizing the transmission energy. We can also observe that the multipath routing is the most adopted routing protocol and that the considered QoS parameters differ from one solution to another. Most of the proposed solutions with an optimization problem formulation take into account the capacity of the links (even fixed or not) in order to transmit the data from the source to the destination. While in the solutions proposed without an optimization problem formulation the main considered parameter is the energy of the next hop forwarding node.

2.2.4/ Data processing axis *Versus* data routing axis:

From the different reviewed approaches, we can observe that the data processing and data routing have been addressed separately. In fact, in the data processing approaches the main parameters that were considered are the encoding power and the resultant data size. The main objective, of this axis, was to optimally find a balance between the two latter in order to ensure the desired video quality at the destination level while maximizing the network lifetime. Even if the energy consumed during data communication was considered, however, the routing matrix was considered as an input. In contrast, in the data routing axis the main parameters that were considered are the link capacity, the delay and the communication energy. The aim, of this axis, was to minimize as much as possible the energy consumed during the communication phase, in other terms, what is the best downstream node(s) that ensures an efficient data transmission in order to maximize the network lifetime. However, the energy consumed during the data compression was not considered, the data rate was almost time fixed and the distortion was neglected in the most data routing axes approaches.

In the both axes, ignoring the routing phase in the data processing axis, and ignoring the compression level and the distortion that can result while considering a fixed data rate in the data routing axis, can lead to results drastically different from realistic ones.

2.3/ Conclusion

This chapter has presented an overview of the network lifetime maximization approaches in wireless multimedia sensor networks. In analyzing these approaches, we have identified different solutions based on the optimization problem formulation and others not. We have particularly noted that the network lifetime maximization problem was solved separately through two main axes: the data processing axis and data routing axis. The synthesis following this study allowed us to determine the direction of our work in order to propose an efficient solution (based on an optimization problem formulation) which takes into account the main parameters of the two axes.

In the next part II of this dissertation, we present step by step the realization of this solution.

II

CONTRIBUTIONS

3

Maximizing Network Lifetime in Wireless Video Sensor Networks Under Quality Constraints

3.1/ Introduction

This chapter focuses on finding a trade-off between the encoding power at the sources nodes and the visual quality perceived at the sink. We recall that multimedia data should be compressed, prior to transmission. However, as the quality is proportional to the volume and the latter is inversely proportional to consumed resources, mainly energy, the issue is consequently how to balance the video data encoding *versus* the perceived video quality at the sink, while maximizing the overall network lifetime. In other words, the research question to address is: *How the network can find such a trade-off between the desirable visual quality at the sink and the available network's resources, mainly energy and bandwidth, in order to prolong its lifetime as long as possible?*

The closest work to our approach is the one presented in [54] (chapter 2, subsection 2.1.1.1). Similarly, we investigate the problem of distributed network lifetime maximization by considering jointly video encoding and source rates. Nevertheless, the modeling proposed in [54] may lead to unfeasible solutions (*i.e.*, no resolution can be found).

To this end, we propose a fully distributed algorithm, that considers the problem of allocating the resources in a wireless video sensor network, in a way to ensure a trade-off between both: the encoding power and the source rate at each node, while serving the desired video quality requirement. In opposition to the approach presented in [54], our algorithm, of distributed nature, is ensured to find such a trade-off whatever the initial network configuration is.

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3.2/ Network model

We consider a video sensor network consisting of $\mathcal{N}$ multimedia sensors. These tiny devices have to not only capture and collect the relevant information, but also to process these latter in an optimal way (*i.e.*, taking into account the limited resources of the video nodes) in order to maximize the network lifetime while respecting the desired video quality at the destination level. Thus, our network can be defined as follows:

- An oriented graph $G(\mathcal{V}, \mathcal{L})$, where $\mathcal{V} = \{h_0, \ldots, h_{\mathcal{N}-1}\}$ is a set of video sensor nodes and $\mathcal{L} = \{l_{ij} \mid h_i, h_j \in \mathcal{V}\}$ is a set of oriented links.
- Two routing matrices a^+_{il} and a^-_{il} of size $\mathcal{N} * \mathcal{L}$ denote the matrices of outgoing links and incoming links, respectively. Where the ith row represents the ith path, while the lth column represents the lth link, whose elements are defined as: a^+_{il} (resp. with a^-_{il} matrix) equals to 1, if a given link l is an outgoing link from i (resp. with an incoming link) and 0 otherwise. The construction of a^+_{il} and a^-_{il} is based on the Euclidean distance to the sink. More formally, if the Euclidean distance of j (neighbor of i through the link l) to the sink is *less* than the Euclidean distance of i to the sink, then, the $a^+_{il} = 1$ and $a^-_{jl} = 1$.
- From the a^+_{il} and a^-_{il} matrices, a general routing matrix a_{il} of size $\mathcal{N} * \mathcal{L}$ can be formulated as the following: $a_{il} = a^+_{il} - a^-_{il}$.

Each video sensor h has a communication range denoted *ComRange*, and generates data traffic with source rate R_h after capturing and encoding a given video. The generated traffic R_h can be forwarded directly to the sink, if the latter is in the communication range of node h. Otherwise, node h needs to use a multi-hop communication. In other words, it forwards the generated traffic R_h to its one hop neighboring nodes that will proceed similarly until reaching the sink node. Thus, each intermediate node i that contributes to the data routing of node h needs to use its own memory. Therefore, the flow conservation [54], denoted η_{hi}, at each node can be formulated as follows:

$$\eta_{hi} = \sum_{l \in \mathcal{L}} a_{il} x_{hl} = \begin{cases} R_h & \text{if } i \text{ is the source of the traffic} \\ -R_h & \text{if } i \text{ is the sink} \\ 0 & \text{otherwise.} \end{cases} \tag{3.1}$$

where x_{hl} represents the data rate, originated from node h, at link l.

3.3/ Network Assumptions

We consider a network composed by 9 nodes, numbered from 0 to 9 and randomly deployed in $50 * 50$m. In this contribution we assume the following:

- We assume that the deployed nodes know their own coordinates as well as the coordinates x and y of the sink. The sink does not know the coordinates of the nodes.
- The interferences were treated by omnet++ simulator.

- The links capacity were not considered at this stage.
- The routing matrix is predefined, in other terms, the latter is considered as an input to the system.
- The transmission rate (R_h and x_{hl}) is not the same for the network nodes. The latter will be defined for each node separately using the optimization steps.

3.4/ Theoretical Background

As previously mentioned, video sensor networks suffer from very specific constraints mainly related to the multimedia data that must be processed before being transmitted. Among these constraints, The energy consumption is the main focus. For this, and before going further, in this section, we present the most operations consuming in term of energy and that can be defined into two levels: **a)** at the video node level, **b)** at the network level.

3.4.1/ Node Power Consumption Model

The video compression is a complex task that consumes energy and hence impacts the overall energy consumption of the network. For this reason, in this chapter, we distinguish three types of tasks: (a) video encoding, (b) data transmission and (c) data reception. For each type of these tasks, we provide, hereafter, the corresponding analytical model that will be used throughout this chapter:

3.4.1.1/ Video encoding power consumption

The main objective here is to consider and minimize as much as possible the video distortion, since the distortion level is highly influenced by the video encoding. In order to cope with this problem, authors in [56] have analyzed the consumption of the video encoder. To do so, the first step was to design a power-scalable video encoding architecture, and then, they analyzed the relationship between the power consumption and the Rate-Distortion (R-D) model (usually used in scalar data transmission). At the end of these two steps a Power-Rate-Distortion (P-R-D) analytical model was formulated as follows:

$$D_h = \sigma^2 e^{-\gamma . R_h . P_{sh}^{2/3}}, \tag{3.2}$$

where σ^2 is the average input variance, D_h is the encoding distortion, and γ is the encoding efficiency coefficient, R_h is the source rate and P_{sh} is the encoding power (*i.e.*, the power consumed during the data compression). This model introduces the trade-off between the encoding power consumption of the source node and the generated video traffic when targeting a fixed distortion (*i.e.* targeting the desired video quality at the sink). We can also observe that, if we highly increase the encoding power P_{sh}, then R_h decreases and the distortion D_h increases.

Thus, the required encoding power should be determined and can be derived from (3.2) as the following:

$$P_{sh} = \left(\frac{\ln(\sigma^2) - \ln(D_h)}{\gamma * R_h} \right)^{\frac{2}{3}}. \tag{3.3}$$

3.4.1.2/ Transmission power consumption

Using the power Consumption model presented in [123], the required power for data transmission from node i is formulated as:

$$P_{ti} = \sum_{l \in \mathcal{L}} a_{il}^{+} * (\alpha + \beta d_l^{n_p}) * \sum_{h \in \mathcal{V}} x_{hl}, \tag{3.4}$$

where α and β are transmit electronics parameters, d_l is the Euclidean distance between the transmitter and the receiver, n_p is the path-loss exponent [99] and $\sum_{h \in \mathcal{V}} x_{hl}$ corresponds to the aggregate rate transmitted through link l. For simplicity, we define a novel constant $c_l^s = \alpha + \beta d_l^{n_p}$ that will be used in the rest of this work.

3.4.1.3/ Reception power consumption

Using the same power Consumption model, the required power needed for data reception at node i can be formulated as:

$$P_{ri} = c^r * \sum_{l \in \mathcal{L}} a_{il}^{-} * \sum_{h \in \mathcal{V}} x_{hl}, \tag{3.5}$$

where c^r is the radio receiver energy consumption cost.

Thus, the total power dissipation at node i can be formulated as:

$$P_i = P_{sh} + P_{ti} + P_{ri} \tag{3.6}$$

where $P_{sh} = 0$, if i is the sink node (*i.e.*, $i = |\mathcal{N}| - 1$), in other terms if i is not a video sensor node.

3.4.2/ Network Power Consumption Model

Depending on the target application and its context, several definitions of the network lifetime can be formulated. In this dissertation, we rely on critical applications in which the energy depletion of the first node leads to the death of the whole network. More formally, and by assuming that each node i has initial energy denoted B_i, the network lifetime T_{net} is defined as:

$$T_{net} = \min_{i \in \mathcal{N}} B_i / P_i \tag{3.7}$$

3.5/ Problem formulation

Let us recall that our goal is to find a distributed algorithm that ensures an optimal trade-off between the allocated resources and the desired video quality at the sink level. Hence, we aim to solve the following problem in a fully distributed manner:

$$
\begin{aligned}
\max_{(x,R,P_s)} \quad & \mathrm{T}_{net} \\
\text{subject to} \quad & \sum_{l \in \mathcal{L}} a_{il} x_{hl} = \eta_{hi}, \quad \forall h \in \mathcal{V} \;\; \forall i \in \mathcal{N} \\
& \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \le D_h, \quad \forall h \in \mathcal{V} \\
& T_{net} = \min_{i \in \mathcal{N}} (B_i / P_i), \\
& x_{hl} \ge 0, R_h \ge 0, P_{sh} > 0.
\end{aligned}
\tag{3.8}
$$

The first constraint reflects the flow conservation law maintained at each node. The second constraint ensures the respect of the desired video quality expected at the sink, by keeping the balance between the encoding power and resultant rate under the upper bound (threshold) of the video distortion D_h [56] in MSE. The third constraint presents the network lifetime with respect to the minimum node lifetime (*i.e.*, it models the energy conservation at each sensor node). The rest of constraints ensures that all the variables remain positive.

Thus, the problem in (3.8) can be expressed by the minimization of the maximum ratio of power consumption to residual energy at each node, by defining $q = 1/T_{net}$. This latter can be interpreted as the inverse lifetime of the network and should satisfies $q \ge 1/T_{min}$. Then, the problem in (3.8) can be rewritten as:

$$
\begin{aligned}
\min_{(q,x,R,P_s)} \quad & \mathrm{q} \\
\text{subject to} \quad & \sum_{l \in \mathcal{L}} a_{il} x_{hl} = \eta_{hi}, \quad \forall h \in \mathcal{V} \;\; \forall i \in \mathcal{N} \\
& \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \le D_h, \quad \forall h \in \mathcal{V} \\
& P_i \le q B_i, \quad \forall i \in \mathcal{N} \\
& x_{hl} \ge 0, R_h \ge 0, P_{sh} > 0.
\end{aligned}
\tag{3.9}
$$

This linear programming formulation can be solved using the subgradient algorithm, after ensuring the convexity of the problem and defining Lagrangian function (using Lagrange multipliers). However, to solve this problem in a fully distributed manner, one way is to completely decentralize the global variable q.

3.6/ Fully Distributed resolution

In this section, we describe a way to resolve the problem in a fully distributed manner. To this end, auxiliary variables, $q_i (\forall i \in \mathcal{N})$, have been introduced, such that: $1/q_i \le T_i (\forall i \in \mathcal{N})$. However, this latter should be followed by an additional constraint that enforces all q_i's to be equal, *i.e.*, $\sum_{i \in N} a_{il}.q_i = 0$ $(\forall l \in \mathcal{L})$.

On the other hand, the primal solution is not immediately available since the objective function is not strictly convex with respect to all the primal variables, and thus, the dual functions are non-differentiable. First, we can change the primal objective function q_i to q_i^2, since minimize q_i is equivalent to minimize $q_i^2 (\forall i \in \mathcal{N})$. Thus, the problem in (3.9) can be reformulated as follows:

$$
\begin{aligned}
\underset{(q,x,R,P_s)}{\text{minimize}} \; & \textstyle\sum_{i \in N} q_i^2 \\
\text{subject to} \; & \sum_{l \in \mathcal{L}} a_{il} x_{hl} = \eta_{hi}, \quad \forall h \in \mathcal{V} \;\; \forall i \in \mathcal{N} \\
& \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \le D_h, \quad \forall h \in \mathcal{V} \\
& P_i \le q_i B_i, \quad \forall i \in \mathcal{N} \\
& \sum_{i \in \mathcal{N}} a_{il} q_i = 0, \quad \forall l \in \mathcal{L} \\
& x_{hl} \ge 0, R_h \ge 0, P_{sh} > 0, q_i > 0.
\end{aligned}
\tag{3.10}
$$

Second, we ensure the convexity of the primal variables (*i.e.*, the source rate R_h, the link rate x_{hl}, and the encoding power P_{sh}) by introducing the following powers to the corresponding functions: α_r, α_x, and α_p respectively. Then, to keep their impact as minimal as possible on the objective function, a small quadratic regularization terms (namely, δ_r, δ_x, and δ_p) are introduced. Finally, to constitute a convex optimization problem with respect to all decision variables, the objective function of (3.10) should be reformulated as the following:

$$
\sum_{i \in \mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^{\alpha_x} + \delta_r \sum_h R_h^{\alpha_r} + \delta_p \sum_h P_{sh}^{\alpha_p}, \tag{3.11}
$$

where $h \in \mathcal{V}$ and $l \in \mathcal{L}$.

3.6.1/ Dual Problem

After ensuring the convexity of the system. We claim that Lagrangian Dual based methods [93] are appropriate to solve such a problem. Therefore, we form the Lagrangian function by introducing the Lagrange multipliers (namely, u_i, v_h, $\lambda_{h,i}$, w_l) with respect to all the constraints of the optimization problem in (3.10). Thus, the resulting Lagrangian is:

$$
\begin{aligned}
& L(q, x, R, P_s, u, v, \lambda, w) = \\
& \textstyle\sum_{i \in \mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^{\alpha_x} + \delta_r \sum_h R_h^{\alpha_r} + \delta_p \sum_h P_{sh}^{\alpha_p} \\
& + \textstyle\sum_{h \in \mathcal{V}} \sum_{i \in \mathcal{N}} u_{hi} \left(\sum_{l \in \mathcal{L}} a_{il} x_{hl} - \eta_{hi} \right) \\
& + \textstyle\sum_{h \in \mathcal{V}} v_h \left(\dfrac{\ln(\sigma^2 / D_h)}{\gamma P_{sh}^{2/3}} - R_h \right) \\
& + \textstyle\sum_{i \in \mathcal{N}} \lambda_i \left(P_i - q_i B_i \right) \\
& + \textstyle\sum_{l \in \mathcal{L}} w_l \left(\sum_{i \in \mathcal{N}} a_{il} q_i \right).
\end{aligned}
\tag{3.12}
$$

By relaxing the total power consumption P_i as defined in (3.6), the formulation becomes:

$$\begin{aligned} &L(q, R, x, P_s, u, v, \lambda, w) = \\ &\textstyle\sum_{i\in\mathcal{N}} \left(q_i^2 + q_i \left(\sum_{l\in\mathcal{L}} a_{il} w_l - \lambda_i B_i\right)\right) \\ &+ \textstyle\sum_{h\in\mathcal{V}} \left(v_h \dfrac{\ln(\sigma^2/D_h)}{\gamma P_{sh}^{2/3}} + \lambda_h P_{sh} + \delta_p P_{sh}^{\alpha_p} \right) \\ &+ \textstyle\sum_{h\in\mathcal{V}} \sum_{l\in\mathcal{L}} \left(\delta_x x_{hl}^{\alpha_x} + x_{hl}(c_l^s \sum_{i\in\mathcal{N}} \lambda_i a_{il}^+ + c^r \sum_{i\in\mathcal{N}} \lambda_i a_{il}^- + u_{hi} a_{il})\right) \\ &+ \textstyle\sum_{h\in\mathcal{V}} \left(\delta_r R_h^{\alpha_r} - v_h R_h - \sum_{i\in\mathcal{N}} u_{hi} \eta_{hi}\right). \end{aligned} \tag{3.13}$$

Then, the dual problem can be written as follows:

$$\begin{aligned} \min_{(q,x,R,P_s)} \quad & \mathrm{L}(q, x, R, P_s, u, v, \lambda, w) \\ \text{subject to} \quad & v_{\forall h\in\mathcal{V}} \geq 0, \\ & \lambda_{\forall i\in\mathcal{N}} \geq 0. \end{aligned} \tag{3.14}$$

3.6.2/ Closer look to convexity

The regularization factor of the encoding power consumption (δ_p) if not efficiency introduced, it will be updated by: $P_{sh}^{(k)} = \arg\min_{P_{sh}>0} \left(v_h^{(k)} \dfrac{\ln(\sigma^2/D_h)}{\gamma P_{sh}^{2/3}} + \lambda_h^{(k)} P_{sh} \right)$. [54]

The function inside the $\arg\min$ is strictly convex if and only if ${\lambda_h}^{(k)}$ is not null. This asymptotic configuration may arise due to the definition of λ_h. Worth, in this case, the function is strictly decreasing and the minimal value is obtained when P_{sh} is the infinity as shown in Figure 3.1 where λ_h is null.

Thus, the method follows its iterative calculus with an arbitrarily large value for $P_{sh}^{(k)}$. This leads to a very slow convergence, if the latter is feasible (*i.e.*, select specific parameters).

Let us now describe how to find all of δ_r, δ_x and δ_p, and Let us focus on the function retrieved from (3.13) which is defined over $\mathbb{R}^{+*}$ with:

$$P_{sh} \mapsto k.P_{sh}^{-2/3} + \lambda_h P_{sh} + \delta_p P_{sh}^{\alpha_p},$$

where the scalar k is $\frac{v_h \ln(\sigma^2/D_h)}{\gamma}$. First order and second order derivatives of this function are respectively equal to:

$-2/3.k.P_{sh}^{-5/3} + \lambda_h + \delta_p.\alpha_p.P_{sh}^{\alpha_p-1}$ and $10/3.k.P_{sh}^{-8/3} + \delta_p.\alpha_p.(\alpha_p - 1).P_{sh}^{\alpha_p-2}$.

Obviously, for any $\alpha_p > 1$, the second order derivative is strictly positive. In this case, the function is convex if the first order derivative has exactly one root over its definition domain.

We are then left to find a value $\alpha_p > 1$ such that the first derivative has exactly one root over $\mathbb{R}^{+*}$. From the second derivative we can see that $\alpha_p = 8/3$ constitutes a convenient choice to solve this issue. This derivative is indeed null if and only if

$$-2/3.k + \lambda_h P_{sh}^{5/3} + \delta_p.8/3.P_{sh}^{10/3} = 0$$

which is a quadratic equation on $P_{sh}^{5/3}$ and whose single root over $\mathbb{R}^{+*}$ is

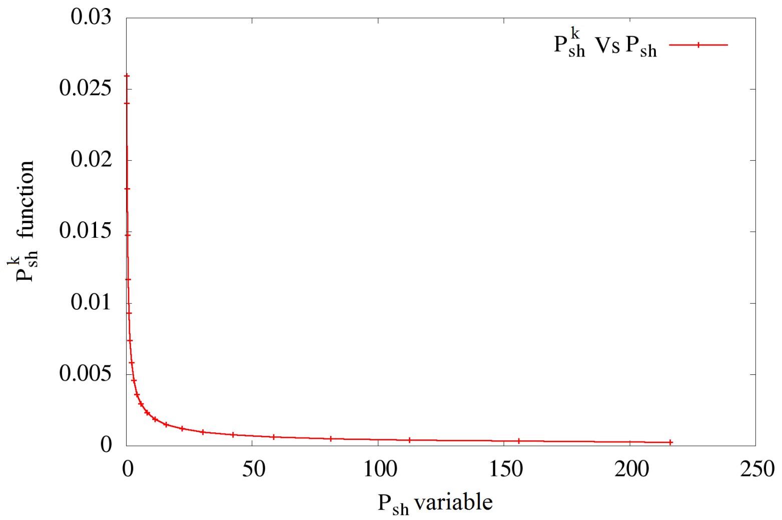


Fig. 3.1: Variation of the $v_h^{(k)} \dfrac{\ln(\sigma^2/D_h)}{\gamma P_{sh}^{2/3}}$ function

$$\left(\frac{-3\lambda_h + \sqrt{(3\lambda_h)^2 + 64\delta_p.v_h/\gamma.\ln(\sigma^2/D_h)}}{16\delta_p}\right)^{\frac{3}{5}}.$$

Finally, we present the resolution of the rest of functions (namely q_i, x_{hl} and R_h) as follows:

The quadratic function $q_i \mapsto q_i^2 + q_i.(\sum_{l\in\mathcal{L}} a_{il}w_l - \lambda_i B_i)$ is obviously convex over q_i and its minimal value is obtained on $\frac{-(\sum_{l\in\mathcal{L}} a_{il}w_l - \lambda_i B_i)}{2}$.

Both functions $x_{hl} \mapsto \delta_x x_{hl}^{\alpha_x} + x_{hl}\sum_{i\in\mathcal{N}} \lambda_i(P_i^c + u_{hi}a_{il})$ and $R_h \mapsto \delta_r R_h^{\alpha_r} - v_h R_h - \sum_{i\in\mathcal{N}} u_{hi}\eta_{hi}$ are of the form $F \mapsto f_0 + f_1 F + f_2 F^{\alpha}$ over $\mathbb{R}^+$, where f_0, f_1, and f_2 are scalars. The first and the second derivatives of this function are respectively $F \mapsto f_1 + \alpha f_2 F^{\alpha-1}$ and $F \mapsto \alpha(\alpha-1) f_2 F^{\alpha-2}$. Obviously the function is convex if $\alpha \geq 2$ and the minimal value is obtained on $(\frac{-g_1}{\alpha})^{\frac{1}{\alpha-1}}$ on such a case.

3.6.3/ Subgradient algorithm

To solve the dual problem in (3.14) the subgradient method [18] is used, and the different Lagrange multipliers can be iteratively calculated, to achieve the desired functionality, as follows:

$$\begin{aligned}
u_{hi}^{k+1} &= u_{hi}^k - \theta^k\left(\eta_{hi}^k - \textstyle\sum_{l\in\mathcal{L}} a_{il}x_{hl}^k\right),\\
v_h^{k+1} &= \max\left\{0, v_h^k - \theta^k\left(R_h^k - \frac{\ln(\sigma^2/D_h)}{\gamma(P_{sh}^k)^{2/3}}\right)\right\},\\
\lambda_i^{k+1} &= \max\left\{0, \lambda_i^k - \theta^k\left(q_i^k B_i - P_{ti}^k - P_{ri}^k - P_{si}^k\right)\right\},\\
w_l^{k+1} &= w_l^k + \theta^k \textstyle\sum_{i\in\mathcal{N}} a_{il}q_i^k,
\end{aligned} \tag{3.15}$$

where θ^k represents the step size defined by: $\theta^k = \rho/\sqrt{k}$, where $\rho > 0$ and $k > 0$.

Since the objective of this chapter is to reduce all the computation steps to increase the network lifetime, we can observe that, the functions to be minimized are all differentiable, and thus, can be computed in only one step as in the following:

$$
\begin{aligned}
q_i^k &= \max\left\{\epsilon, \frac{-(\sum_{l\in\mathcal{L}} a_{il}w_l - \lambda_i B_i)}{2}\right\},\\
P_{sh}^k &= \max\left\{\epsilon, \left(\frac{-3\lambda_h^k + \sqrt{(3\lambda_h^k)^2 + 64\delta_p v_h^k/\gamma \ln(\sigma^2/D_h)}}{16\delta_p}\right)^{\frac{3}{5}}\right\},\\
R_h^k &= \max\left\{0, \frac{{v_h}^k}{2\delta_r}\right\},\\
x_{h,l}^k &= \max\left\{0, \frac{-\sum_{i\in\mathcal{N}}\left(c_l^s\lambda_i^k a_{il}^+ + c^r\lambda_i^k a_{il}^- + u_{hi}^k a_{il}\right)}{2\delta_x}\right\},
\end{aligned}
\tag{3.16}
$$

for any $h \in \mathcal{V}$, $i \in N$, and $l \in \mathcal{L}$.

Finally, our proposed algorithm, executed by each node i, iteratively computes/updates the above primal-dual variables, using its own variables and those received from its one-hop neighbors, denoted by *Nbrs*$_i\}$. The algorithm stops when the range of neighboring $\{q_j \mid j \in$ *Nbrs*$_i$ with its own q_i (*i.e.*, $S = \{q_j \mid j \in$ *Nbrs*$_i\} \cup \{q_i\}$) is smaller than a given threshold T:

$$\frac{\max_{i\in S}\{q_i\}}{\min_{i\in S}\{q_i\}} - 1 \leq T. \tag{3.17}$$

Where $T = 10^{-n}$, and $n = \{1, ..., 5\}$ for instance. Algorithm 1 resumes our proposal.

Algorithm 1 Distributed optimization algorithm

Initialize: Set $k = 1$ and $P_{sh}^{(k)}$, $R_h^{(k)}$, $x_{hl}^{(k)}$, $q_i^{(k)}$, $u_{hi}^{(k)}$, $v_h^{(k)}$, $\lambda_h^{(k)}$, $w_l^{(k)}$ to any initial point.
step 1:
each node $i \in \mathcal{N}$ **and** $h \in \mathcal{V}$
  calculates $u_{hj(j\in Nbrs_h)}^{(k+1)}$, $v_h^{(k+1)}$, $\lambda_h^{(k+1)}$, $w_l^{(k+1)}$, $P_{sh}^{(k+1)}$, $R_h^{(k+1)}$, $q_i^{(k+1)}$;
  transmits $\lambda_h^{(k+1)}$ and $q_i^{(k+1)}$ to one-hop neighboring;
end step 1
At the reception of $\lambda_h^{(k+1)}$
step 2:
each node $h \in \mathcal{V}$
  calculates $x_{hl}^{(k+1)}$;
  transmits $x_{hl}^{(k+1)}$ to one-hop neighboring;
end step 2
repeat
  step 1
  step 2
until $\{$the range of $q_i \leq T\}$

3.7/ Simulation results

In this section, we analyze and evaluate the effectiveness and the performance of our distributed algorithm, through simulations, using the topology given in Figure 3.2. Our network consists of $N = 10$ nodes, randomly deployed in a $50 \times 50m^2$ region, and numbered from 0 to 9, where the sink is presented by the ninth node, while the rest of nodes present the video sensor nodes (*i.e.*, $h = \{0, ..., 8\}$) and $L = 22$ links. Each node has a transmission range of 30 m. Considering a lossless transmission channel (all the sent packets are received with 100% of reliability), our algorithm was implemented through MiXiM framework [71], on top of OMNET++ simulator [119].

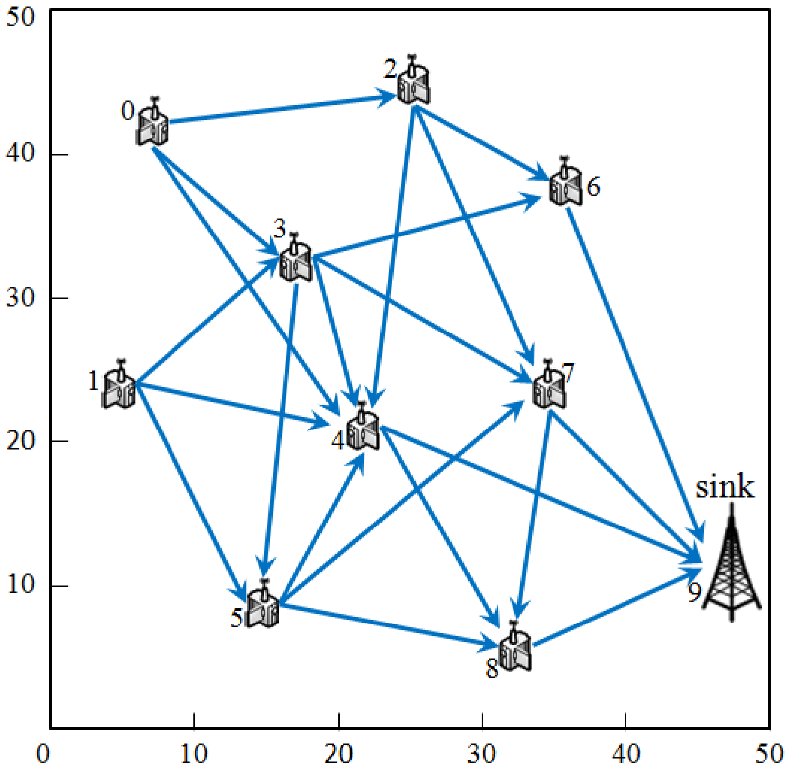


Fig. 3.2: The used topology in WVSN.

The overall simulation parameters, with their notations and default values, are presented in Table 3.1. In addition to the units in table 2.3, presented in chapter 2, section 2.2.1, the remainder units of the used parameters in this dissertation are completed in table 3.2.

In order to be as close to reality as possible, we have studied several visual sensors platforms among them *CITRIC* [24], *Panoptes* [44] and *Meerkats* [20]. As we target a monitoring and surveillance visual application, similarly to *Panoptes*, we have used their corresponding visual sensor settings. Hence, we have initialized the encoding power, P_{sh}, of each node by 3.05 W, as reported in [44].

3.7.1/ Convergence results

Before proceeding any further, it would be appropriate to analyze the impact of the convergence threshold on the network lifetime.

Let us recall that, the distributed solution is satisfied if and only if the same value of q_i can be achievable by all nodes at the end of the optimization steps. However, selecting stop criterion of the optimization iterations plays an important role in network lifetime, since to pass from one precision to another requires a significant number of iterations, and hence

Table 3.1: Configuration of model parameters in a WVSN [54]

Notation	***Description***	***Value***
σ^2	Variance of video encoder (in terms of MSE)	3500
γ	Encoding efficiency coefficient	55.54 $W^{3/2}.Mb^{-1}.s^{-1}$
B_i	Initial energy at each node	5.0 MJ
$\delta_x, \delta_r, \delta_p$	Regularization factors	0.2
ρ	step size parameter	0.15
D_h	Distortion of an encoding frame (in terms of MSE)	100
α	Energy cost of the transmit electronics	0.5 $J.Mb^{-1}$
β	Coefficient term of the transmit amplifier	$1.3 * 10^{-8}$ $J.Mb^{-1}.m^{-4}$
n_p	Path loss exponent	4
c^r	Energy consumption cost of radio receiver	0.5 $J.Mb^{-1}$

Table 3.2: Table of units

Notation	***Description***	***Units***
q_i	Auxiliary variable	$1/Ms$
c_l	Capacity of link l	Ghz
x_{hl}	The bits sent on each link	$Mbps$

more activity duration and power consumption, as shown in table 3.3. For example, the node 0 (in table 3.3) has to consume 22600 s of its lifetime and this only to gain more precision (*i.e.*, from 10^{-2} to 10^{-5}) with respect to the common variable q.

To select such a threshold, it is also necessary to ensure the stability of both of: the encoding powers (P_{sh}) and the source's rate (R_h), since the main objective is to find the optimal trade-off between these two latter. Table 3.4 depicts the required time (in minutes) to reach each threshold (from 10^{-1} to 10^{-4}) in the worst case (*i.e.*, the latest node that converges to the common variable q, here node 3).

We can observe that, both of the P_{s3} and R_3 reach the 10^{-4} threshold, even before the q_3 reaches the 10^{-2} convergence threshold.

Thus, in the following, we consider the system as completely stable when the maximum variation between the q_i is $T = 10^{-2}$, allowing us to gain $16630s$ in node lifetime (considering the node with the lowest lifetime, *i.e.*, node 5), and thus in network lifetime, compared to that obtained at the 10^{-5} convergence threshold.

The convergence of the auxiliary variables q_i, used in our algorithm, to a common variable q with a threshold set to 10^{-2} is presented in Figure 3.4. While Figure 3.3.(a) and Figure 3.3.(b) show the stability of both P_{sh} and R_h, respectively.

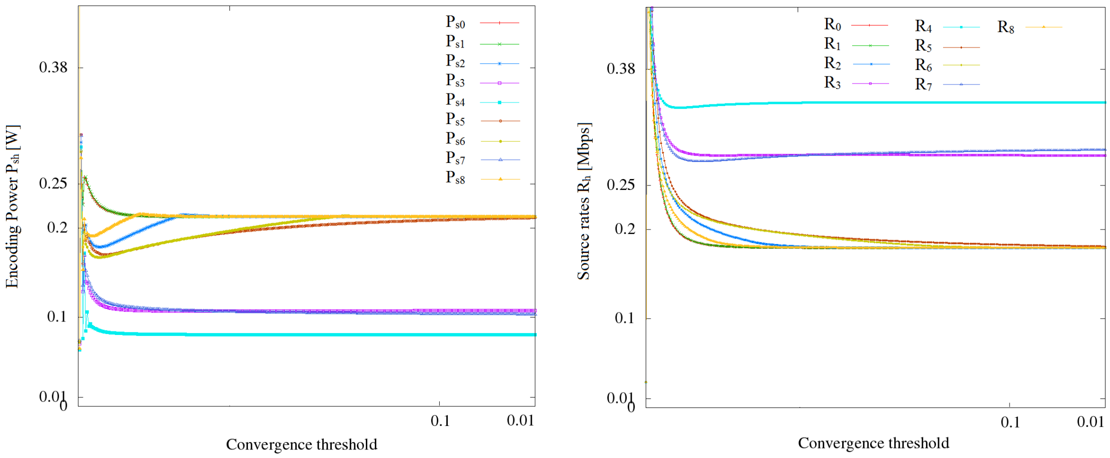
Let us now explain the difference between the values of P_{sh} (resp. R_h) at each node. From Figure 3.3.(a), we can observe that, highest is the incoming data traffic to the given node, less is its encoding power. These results were expected, since these nodes have to ensure the transfer of, not only their own data but also those coming from their neighbors. And thus, should minimize their encoding power and maximize their rate, which can be confirmed by Figure 3.3.(b), where the nodes with highest incoming data have the highest source rates compared to the other nodes.

Table 3.3: convergence threshold impact

Node	***Convergence threshold passage***	***Lifetime requirement "s"***
node 0	from 10^{-2} to 10^{-5}	22600
node 1	from 10^{-2} to 10^{-5}	7600
node 2	from 10^{-2} to 10^{-5}	27300
node 3	from 10^{-2} to 10^{-5}	110420
node 4	from 10^{-2} to 10^{-5}	816100
node 5	from 10^{-2} to 10^{-5}	16630
node 6	from 10^{-2} to 10^{-5}	27600
node 7	from 10^{-4} to 10^{-5}	14700
node 8	from 10^{-4} to 10^{-5}	4080

Table 3.4: Configuration of model

Variables/Threshold	0.1	0.01	0.001	0.0001
q_3 (min)	0.85	12.99	24.94	44.37
P_{s3} (min)	0.224	0.657	5.55	8.824
R_3 (min)	0.42	0.491	11.25	12.75



(a) (b)

Fig. 3.3: (a)Encoding powers, (b)Source rates versus the convergence threshold

3.7.2/ Optimization cost

In this subsection we analyze the cost of the optimization steps on both energy and duration at each node.

3.7.2.1/ Energy cost

We conducted empirical studies to evaluate the cost of the optimization on the energy consumption at each node. The percentage of Battery B_{Pi} that is consumed by the optimization steps is defined as follows: $B_{Pi} = (100 * E_i)/B_i$, where E_i is the energy, consumed during this stage.

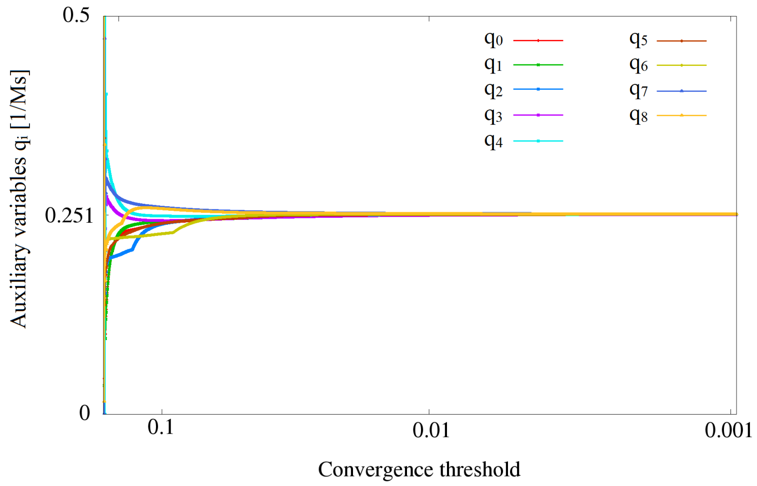


Fig. 3.4: Auxiliary variables.

During the optimization process, to update the dual variables described in equation (3.15), it is indeed sufficient to have the neighborhood values of x_{hl} and q_i since both are multiplied by a_{il}. Similarly for the primal variables described in equation 3.16, where only λ_i is needed for the updates. After that, the node i transmits its own data to the sink with respect to the values of both encoding power and link rate.

Thus, the power consumption for the optimization steps P_{oi} (*i.e.*, communication of the needed variables for optimization) is:

$$P_{Oi} = P_{tOi} + P_{rOi} = \sum_{l \in \mathcal{L}} a_{il}{}^{+} c_l{}^{s} (\mathcal{S}(x_{hl}) + \mathcal{S}(\lambda_i) + \mathcal{S}(q_i)) + c^r \sum_{l \in \mathcal{L}} a_{il}{}^{-} (\mathcal{S}(x_{hl}) + \mathcal{S}(\lambda_i) + \mathcal{S}(q_i)), \tag{3.18}$$

where, $\mathcal{S}(X)$ denotes the size of X in Mb.

Figure 3.5 depicts the percentage of battery consumption of each node, for each threshold $T \geq 10^{-3}$ used in equation (3.17). It is observed that the optimization steps consume less than 0.03% of the total battery, at the chosen 10^{-2} convergence threshold. Thus, it can be concluded that the steps of optimization consume fewer even a negligible energy.

3.7.2.2/ Optimization duration

In some video sensor network applications, the optimization convergence duration is extremely important, not only to achieve a maximum network lifetime, but also to make the network operational as soon as possible.

Thus, depending on the needs of the application in terms of rapidity and precision (with respect to q_i) of convergence, the system can be impacted in term of duration. Figure 3.6 presents the optimization steps duration (in minutes) for each threshold $T \geq 10^{-3}$ presented in equation (3.17). It can be observed that more is the need to gain precision, the larger is the optimization duration.

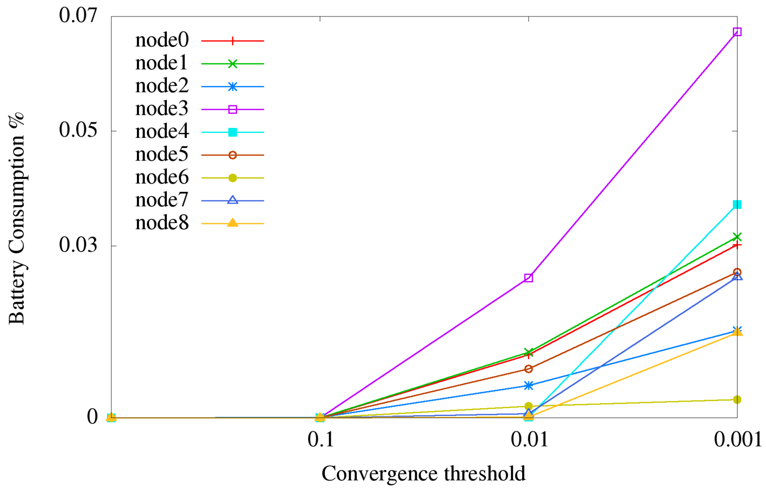


Fig. 3.5: battery consumption of optimization steps

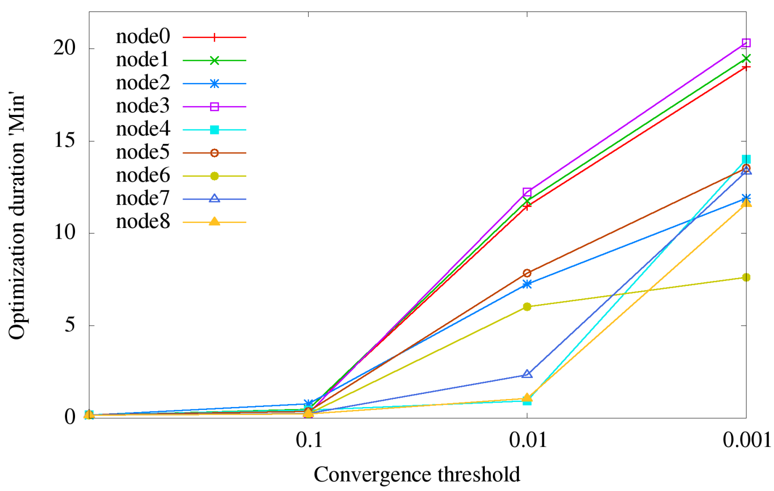


Fig. 3.6: Optimization duration

3.7.3/ IMPROVEMENT

As described in section 3.4, to calculate the network lifetime, we need to calculate the total power consumption P_i, and hence the necessity to initialize the encoding power and links rate at each node. As aforementioned, we initialize the encoding power P_{sh} $(h \in \mathcal{V})$ at 3.05W [44]. After, the initial links rate was chosen randomly between 0.34 and 0.37 (Mb/s) at each node $h \in \mathcal{V}$.

Figure 3.7 shows the node lifetime at each convergence threshold starting from 10^{-1} to 10^{-3} with respect to the common variable q. We can observe a rapid and high increase of the nodes lifetime even before reaching the 10^{-1} convergence threshold. Also, We can observe that after the 10^{-1} convergence threshold, most of the nodes lifetime begins to be steady. However, we cannot trust the system at this stage, since the values calculated and exchanged between nodes at this stage are not yet stable. After the 10^{-2} convergence threshold we can observe that the values of each node lifetime are almost steady (*i.e.*, after this convergence threshold, the system only tries to gain in precision).

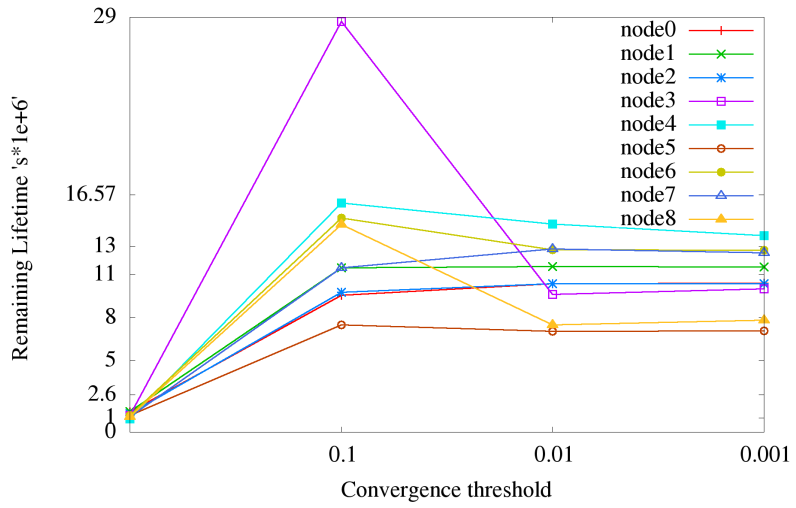


Fig. 3.7: Remaining lifetime after each convergence threshold

In Figure 3.8, we can observe that with our optimization steps, and by imposing a trade-off between P_{sh} and R_h, we have increased the network lifetime by at least 6.08 times compared to the network lifetime without optimization (considering the minimum node lifetime *i.e.*, node 5). Thus, it demonstrates that the proposed design effectively increases the network lifetime.

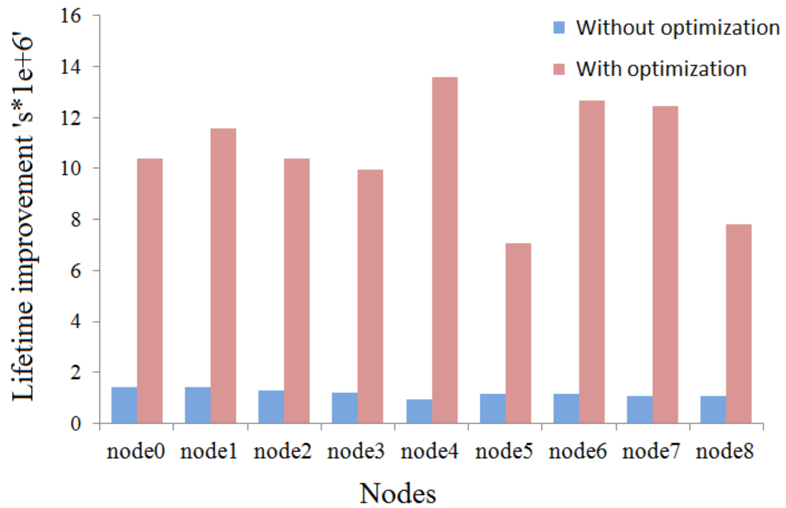


Fig. 3.8: Remaining lifetime comparison

3.7.3.1/ Gradient Vs argmin methods impact

Let us recall that in [54], He et al. have also proposed a resolution which is based on the Lagrangian and subgradient methods. However, they used the argmin's computations. Among state of the art, for this optimization step, there is: L-BFGS-B algorithm [22], truncated Newton algorithm [89], Constrained Optimization BY Linear Approximation (COBYLA) method [96], etc. However, all these methods suffer from being itera-

Convergence Threshold	10^{-5}	$1.67.10^{-5}$	$2.78.10^{-5}$	$4.64.10^{-5}$	$7.74.10^{-5}$	$1.29.10^{-4}$	$2.15.10^{-4}$	$3.59.10^{-4}$	$5.99.10^{-4}$	0.001
Improvement	97.47%	97.48%	96.70%	97.20%	96.62%	96.99%	96.71%	96.80%	96.37%	95.90%

Table 3.5: Convergence Times for Gradient and Argmin Methods

tive approaches, and each iteration may include many steps of computation to obtain an approximation of the minimal value.

The performance of the derivative and the argmin computing has been evaluated on a set of experiments. For 10 thresholds T, such that $1E-5 \leq T \leq 1E-3$, we have executed 10 times the gradient and the argmin approaches. Table 3.5 summarizes the percentage of the execution time reduction using the derivative approach compared to the argmin one. We can see that with the derivative approach we reduce the execution time requirement by 97.47% (at a 10^{-5} convergence threshold) compared to the argmin approach. Among implementations of argmin approaches, we have retained the COBYLA one since it does not require any derivative to be executed.

3.8/ Conclusion

WVSNs are more constraint than traditional wireless sensor networks in terms of power consumption. Therefore, energy efficiency is considered as the primary attributes in a such networks to prolong the network lifetime. Optimization methods have shown a great potential to formulate, develop and define the optimum power and rate allocation while maintaining the desired video quality and maximize the network lifetime.

In this chapter, we proposed a fully distributed algorithm that maximizes the network lifetime by jointly optimizing the encoding power and the source rate in order to meet the desired visual quality. Our algorithm ensured the convergence of the system regardless of the initial configuration in comparison to [54]. In addition, simulation results show the effectiveness of our proposal in reducing till 95% of the total time necessary to find the argmin of the primal functions in comparison to [54].

In the next chapter we will extend our proposal by allowing it to handle a **dynamic change of links capacity**, in order to avoid both: (a) data loss (b) and low network connectivity. In other terms, additional constraints will be addressed.

4

Optimal Power/Rate trade-off for WVSN Lifetime Maximization Under Dynamic Links Capacity

4.1/ Introduction

In WVSN, data are transferred from source nodes to destination node using the multi-hop communication, over unreliable wireless links. One of the main QoS metric, which is the capacity of each link to support data weight (namely, bandwidth), has not been carefully studied, which may lead to complicated problems as: data loosing and very low network connectivity, since the radio range becomes increasingly shorter when data transmission rates are increasingly higher.

Existing work [39, 49, 114, 135] have mainly focused on wireless video sensor networks that use a single transmission link rate. However, channel rates capacity changes from one link to another and from one transmission to another, and the attainable capacity of each one depends on both: **a)** the interference level that can be perceived at the receiver, **b)** and the transmitted data length.

In section 3.5, we studied the maximum achievable network lifetime with unlimited channel capacity. In this chapter, we investigate on multi-rate channel capacity in WVSN by developing a theoretical model to calculate the attainable capacity of each wireless link as it will be described in section 4.3. Then, to deal with the channel transmission error, the retransmission mechanism was chosen which will be detailed in section 4.5.

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4.2/ Network Assumptions

At the difference of the assumptions made in chapter 3.5, in this contribution we cope with the problem of links capacity. The rest of the assumption (namely, the distance from the sink, the interferences, the routing matrix and the different transmission rates) remains the same.

4.3/ PROBLEM FORMULATION AND SOLUTION FOR MAXIMUM NETWORK LIFETIME UNDER MULTIRATE LINKS CONSTRAINT

Channel capacity changes depending on both: noise power and data rate perceived at the receiver. For this, the capacity of the channel C_l at each link l can be formulated, using the Shannon's theorem (1984) as described in [116], as the following:

$$C_l = 2W \log_2 \sqrt{1 + \frac{P_{rl}}{N_0 W}} \quad \forall l \in \mathcal{L}, \tag{4.1}$$

where W is a measure of the width of a range of frequencies (measured in Hertz), P_{rl} is the reception power, and N_0 is the additive white Gaussian noise.

Before going further, we want to highlight an error that occurred when writing Shannon's formula to calculate the link capacity. Indeed, this formula should be written as shown above. However, when recovering this formula we have forgotten the 2 at the beginning of the equation.

Fortunately, this oversight only limits the field of research and therefore does not affect the validity of our results. Adding the 2 can only improve (but not much) the results already obtained and this after simulation verification. It would have been binding if we had replaced the 2 with a larger value, for example 4.

Thud, it should be noted that in the rest of this dissertation, we have worked with the following formula:

$$C_l = W \log_2 \sqrt{1 + \frac{P_{rl}}{N_0 W}} \quad \forall l \in \mathcal{L}, \tag{4.2}$$

Additionally, each node has a maximum transmission power $P_{t_{max}}$, (resp. reception power $P_{r_{max}}$), that it can't exceed to send (resp. to receive) data. In this work, we consider a homogeneous model (*i.e.*, the same $P_{t_{max}}$ and $P_{r_{max}}$ for all nodes). Thus, two additional constraints should be introduced, to the problem formulation, in order to limit the transmission and reception power of each node as the following:

$$\sum_{l \in \mathcal{L}} a_{il}^{+} P_{t_l} \leq P_{t_{max}} \quad \forall i \in \mathcal{N}, \tag{4.3}$$

$$\sum_{l \in \mathcal{L}} a_{il}^{-} P_{r_l} \leq P_{r_{max}} \quad \forall i \in \mathcal{N}, \tag{4.4}$$

where:

$$P_{t_l} = c_l^s \sum_{h \in \mathcal{V}} x_{hl} \quad \forall l \in \mathcal{L}, \tag{4.5}$$

$$P_{r_l} = c^r \sum_{h \in \mathcal{V}} x_{hl} \quad \forall l \in \mathcal{L}. \tag{4.6}$$

The definition of variables c_l^s, c^r and x_{hl} are the same as that presented in (3.4) and (3.5).

Taking into account the aforementioned constraints, and to integrate the multirate formulation in the mathematical model presented in chapter 3 section 3.6. The optimization problem formulated in (3.10), with the objective function of (3.11), should be reformulated as follows:

$$
\begin{aligned}
\underset{(R,x,P_s,q)}{\text{minimize}}\ & \textstyle\sum_{i\in\mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_{h} R_h^2 + \delta_p \sum_{h} P_{sh}^{8/3} \\
\text{subject to}\ & \sum_{l\in\mathcal{L}} a_{il} x_{hl} = \eta_{hi} \quad \forall h \in \mathcal{V}\ \forall i \in \mathcal{N}, \\
& \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \le D_h \quad \forall h \in \mathcal{V}, \\
& P_{sh} + P_{ti} + P_{ri} \le q_i B_i \quad \forall i \in \mathcal{N}, \\
& \sum_{i\in\mathcal{N}} a_{il} q_i = 0 \quad \forall l \in \mathcal{L}, \\
& \sum_{h\in\mathcal{V}} x_{hl} \le W \log_2 \sqrt{1 + \frac{P_{rl}}{N_0 W}} \quad \forall l \in \mathcal{L}, \\
& \sum_{l\in\mathcal{L}} a_{il}^{+} P_{t_l} \le P_{t_{max}} \quad \forall i \in \mathcal{N}, \\
& \sum_{l\in\mathcal{L}} a_{il}^{-} P_{r_l} \le P_{r_{max}} \quad \forall i \in \mathcal{N}, \\
& x_{hl} \ge 0, R_h \ge 0, P_{sh} > 0, q_i > 0.
\end{aligned}
\tag{4.7}
$$

The Fifth constraint ensures that each data rate sent on each link respects the maximum link capacity. The Sixth and Seventh constraints ensure the respect of the maximum transmission and reception power, respectively, by each node.

Thus, similarly to the network lifetime maximization problem presented in (3.10), we use the primal-dual method [93] to solve the optimization problem (4.7). We first replace each variable P_{ti}, P_{ri}, P_{t_l} and P_{r_l} with its definition respectively, presented in (3.4), (3.5), (4.5), and (4.6). Thus, the Lagrangian function for the optimization problem can be reformulated as the following:

$$
\begin{aligned}
& L(R, x, P_s, q, \eta, v, \lambda, w, \Gamma, \zeta, \mathrm{Z}) = \\
& \textstyle\sum_{i\in\mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_h R_h^2 + \delta_p \sum_h P_{sh}^{8/3} + \\
& \textstyle\sum_{h\in\mathcal{V}} \sum_{i\in\mathcal{N}} u_{hi} \left(\sum_{l\in\mathcal{L}} a_{il} x_{hl} - \eta_{hi}\right) \\
& + \textstyle\sum_{h\in\mathcal{V}} v_h \left(\dfrac{\ln(\sigma^2/D_h)}{\gamma P_{sh}^{2/3}} - R_h \right) \\
& + \textstyle\sum_{i\in\mathcal{N}} \lambda_i \left(P_{sh} + \sum_{l\in\mathcal{L}} a_{il}^{+} c_l^{s} x_{hl} + c^r \sum_{l\in\mathcal{L}} a_{il}^{-} x_{hl} - q_i B_i \right) \\
& + \textstyle\sum_{l\in\mathcal{L}} w_l \left(\sum_{i\in\mathcal{N}} a_{il} q_i \right) \\
& + \textstyle\sum_{l\in\mathcal{L}} \Gamma_l \left(\sum_{h\in V} x_{hl} - W \log_2 \sqrt{1 + \frac{(c^r \sum_{h\in\mathcal{V}} x_{hl})}{N_0 W}} \right) \\
& + \textstyle\sum_{i\in\mathcal{N}} \mathrm{Z}_i \left(\sum_{l\in\mathcal{L}} a_{il}^{+} c_l^{s} \sum_{h\in\mathcal{V}} x_{hl} - P_{t_{max}} \right) \\
& + \textstyle\sum_{i\in\mathcal{N}} \zeta_i \left(\sum_{l\in\mathcal{L}} a_{il}^{-} c^r \sum_{h\in\mathcal{V}} x_{hl} - P_{r_{max}} \right).
\end{aligned}
\tag{4.8}
$$

In addition to the iterative calculation of the Lagrange multipliers described in Section 3.6.3, and using the subgradient method [18], the Lagrange multipliers (namely Γ, Z and

ζ) added in equation (4.8) can be calculated as the following:

$$\begin{aligned}
\Gamma_l^{k+1} &= \max\left\{0, \Gamma_l^k - \theta^k\left(W\log_2\sqrt{1+\frac{P_{rl}^k}{N_0 W}} - \sum_{h\in\mathcal{V}} x_{hl}^k\right)\right\}, \\
Z_i^{k+1} &= \max\left\{0, Z_i^k - \theta^k\left(P_{t_{max}} - \sum_{l\in\mathcal{L}} a_{il}^+ P_{tl}^k\right)\right\}, \\
\zeta_i^{k+1} &= \max\left\{0, \zeta_i^k - \theta^k\left(P_{r_{max}} - \sum_{l\in\mathcal{L}} a_{il}^- P_{rl}^k\right)\right\}.
\end{aligned} \tag{4.9}$$

Finally, the primal variables (q_i^k, P_{sh}^k and R_h) can be calculated as described in Section 3.6.3 to obtain a fully distributed solution.

Let us now focus on the updating of the x_{hl} rate. Contrary to previously presented primal variables, it cannot be directly extracted from equation (4.8) since x_{hl} appears inside nested functions, namely the logarithm and the square root ones. However, by providing x close to 0, $\ln(1+x)$ may be approximated by x. It remains to prove that all along the updating process, this approximation can be applied. We indeed successively have $0 \leq \frac{P_{rl}}{N_0 W} \leq \frac{P_{rmax}}{N_0 W}$. Since, N_0 is equal to 0.5, and the orders of magnitude for $P_{r_{max}}$ and W are some Watt and some GHz, respectively, this bound is less than 10^{-4}. Thus $W\log_2\sqrt{1+\frac{c^r\sum_{h\in\mathcal{V}} x_{hl}}{N_0 W}}$ can be approximated with $\dfrac{c^r\sum_{h\in\mathcal{V}} x_{hl}}{2N_0\ln 2}$.

The rate x_{hl} is defined over $\mathbb{R}^{+*}$ as the value that minimizes the function

$$\begin{aligned}
x_{hl} \mapsto \delta_x x_{hl}^2 + x_{hl}(&\textstyle\sum_{i\in N} u_{hi} a_{il} + c_l^s \sum_{i\in N} \lambda_i a_{il}^+ \\
&+ c^r \textstyle\sum_{i\in N} \lambda_i a_{il}^- + \Gamma_l + c_l^s \sum_{i\in N} Z_i a_{il}^+ \\
&+ c^r \textstyle\sum_{i\in N} \zeta_i a_{il}^- - \frac{c^r \Gamma_l}{2N_0 \ln 2}).
\end{aligned} \tag{4.10}$$

Since such a function is quadratic, it is convex and can be update as follows:

$$\begin{aligned}
x_{hl}^k = \max\Big\{0, &\tfrac{-1}{2\delta_x}(\textstyle\sum_{i\in N} u_{hi}^k a_{il} + c_l^s \sum_{i\in N} \lambda_i^k a_{il}^+ + c^r \sum_{i\in N} \lambda_i^k a_{il}^- \\
&+\Gamma_l^k + c_l^s \textstyle\sum_{i\in N} Z_i^k a_{il}^+ + c^r \sum_{i\in N} \zeta_i^k a_{il}^- - \frac{c^r \Gamma_l^k}{2N_0 \ln 2})\Big\}.
\end{aligned} \tag{4.11}$$

In order to evaluate the performance of our solution, we have also implemented the *DQLM* solution that was proposed in [49]. Thus, and before going further let us give a brief overview of such a solution:

Distributed Quality-Lifetime Maximization in Wireless video sensor networks (DQLM) Authors in [49] have proposed a Semi-distributed quality-lifetime maximization solution in WMSN, where they integrated the distortion model in the objective function instead of considering it as a constraint. The problem was formulated based on Generalized Network Utility Maximization (GNUM) [87], and solved by using the *Proximal Point Algorithm* [19].

Firstly, they have considered a network consisting of N nodes, where $S \in N$ is the source nodes, L is the set of links and $R(s)$ is the routes to the video sensor s. Each of which generated a traffic of rate y_s bit.s^{-1} and transmits the latter through the outgoing links at rates x_r .

Then, the consumed power was divided through two levels: **a)** at the sensor stage for sensing and processing and **b)** at the radio stage for communication.

- **a) The sensor stage power:** Let us firstly explain the energy consuming model for the first level. In fact, the latter was considered and formulated using another Power-Rate-Distortion model [77], in which a video sensor captured and compressed the signal by introducing the encoding distortion $D_s(\sigma_s, y_s)$, where y_s is a bit rate (in bit per pixel), $\sigma_s^{(I)}$ is the intra (I) video encoding mode rate and $\sigma_s^{(P)}$ is the inter (P) video encoding mode rate. Thus, the $D_s(\sigma_s, y_s)$ was formulated as follows:

$$D_s(\sigma_s, y_s) = \delta_s^{(P)}(\delta_s^{(I)}/\delta_s^{(P)})^{\sigma_s}2^{-2y_s} \tag{4.12}$$

  where $\delta_s^{(I)}$ and $\delta_s^{(P)}$ are given as a variance for I and P encoding modes, respectively. However, in (4.12) formulation, the power information is implicit. Thus, authors have written the encoding power as a function of σ_s as $p_s = \sigma_s p_s^{(I)} + (1-\sigma_s)p_s^{(P)}$. Then, they defined $\omega_s = p_s^{(P)}/(p_s^{(P)} - p_s^{(I)})$ and solved for σ_s to extract the I-coding mode rates as $\sigma_s = \omega_s(1 - p_s/p_s^{(P)})$ and replace the latter in (4.12).

  The $D_s(\sigma_s, y_s)$ was then reformulated to obtain the encoding distortion $D_s(p_s, y_s)$ as a function of bit rate (y_s) and encoding power (p_s) as follows:

$$D_s(p_s, y_s) = \eta_s e^{(-\kappa_s p_s)} e^{(-d_1 y_s)} \tag{4.13}$$

$$\kappa_s = \omega_s/p_s^{(P)} \log(\delta_s^{(I)}/\delta_s^{(P)}), \quad \eta_s = \delta_s^{(P)}(\delta_s^{(I)}/\delta_s^{(p)})^{\omega_s}, \quad d_1 = 2\log 2. \tag{4.14}$$

  where κ_s, η_s and d_1 are defined as a constants.

- **b) The radio stage power:** In this part they defined $\varepsilon_{n,l}$ as the energy consumed per bit on link l of node n, and by defining the $P_{tx,l}$ and $P_{rx,l}$ as the transmission and reception powers, respectively, as well as the c_l as the capacity of link l, the $\xi_{n,l}$ formulation is as follows:

$$\xi_{n,l} = \begin{cases} P_{tx,l}/c_l & \text{, if } l \text{ is an outgoing link of node n} \\ P_{rx,l}/c_l & \text{, if } l \text{ is an incoming link of node n} \\ 0 & \text{, otherwise.} \end{cases} \tag{4.15}$$

The network lifetime is defined by the functioning of the system until any of the nodes energy is depleted.

After the powers formulation, the optimization problem formulation was considered and have the following format:

$$\begin{aligned} &\underset{(p,x,v)}{\text{minimize}} \; g(v) - f_1(p_s) - f_2(x) \\ &\text{subject to} \sum_{r\in\mathcal{R}} e_{n,r}x_r + \sum_{s\in S} q_{n,s}p_s \le j_n v, \quad \forall n \in N, \\ &\qquad \sum_{l\in L}\sum_{r\in\mathcal{R}} f_{m,l}(h_{lr}/c_l)x_r \le \varepsilon_m, \quad \forall m \in M, \\ &\qquad p_{min} \le p_s \le p_{max}, x_{min} \le x_r \le x_{max}, v_{min} \le v \le v_{max}. \end{aligned} \tag{4.16}$$

Let us now discuss the problem formulation in (4.16). The objective function is combined of two parts, the first part (*i.e.*, $g(v)$) concerns the network lifetime maximization, where $g(v) = v^2/2\theta$ and v is the inverse network lifetime (which is equal to q in our formulation).

The second part of the objective function (*i.e.*, $f_1(p)$ and $f_2(x)$) concerns the quality of the video after the compression phase, where $f_1(p) = d_2 \sum_s \kappa_s p_s$ and $f_2(x) = d_1 d_2 \sum_{r\in\mathcal{R}} x_r$ which have a direct relation with the encoding distortion function presented in (4.13). In fact, in order to minimize the distortion of the video, the authors aimed to increase the peak signal-to-noise-ratio ($PSNR = 10/(log(10))(log(255^2) - \log(D_s(p_s, y_s))))$ and the latter can be achieved at the minimum of $f(p, x) = \sum_s 10/(log(10)) \log(D_s(p_s, y_s))$. Then, after defining $K = 10/(log(10)) \sum_s \log(\eta_s)$, the objective function, to be minimized, can be formulated as $f(p, x) = K - f_1(p) - f_1(x)$.

Let us know focus on the constraints. The first constraint concerns the power consumption model that combines both, the communication power consumption and the encoding power consumption, while the second constraint concerns the joint rate allocation and medium access.

Due to the luck of strict convexity of such a problem, authors have used the Proximal Point Algorithm [19] to solve it. The main dynamic parameters to be calculated (*i.e.*, the primal variables) in this chapter are: the encoding power (p_s) the source rate to be sent (x_r) and the inverse lifetime (v). Both of the p_s and x_r are calculated in a distributed manner at each video sensor node, while v is calculated at the sink level and fed back to sources.

DQLM drawbacks Even though the proposed DQLM solution ensures the convergence of the system, however the latter has some drawbacks that will be highlighted in the following:

- The transmission and reception powers were fixed which is not realistic especially if the source rate is dynamic, which is the case in DQLM.
- The capacity c_l on each link l was fixed which is also far from being realistic, especially in a wireless context.
- The Lagrangian formula is separable only over power consumption and rate allocation, while to update the Lagrangian multipliers, each node needs to have the inverse lifetime, which is computed in a centralized manner by the sink and sent back to sources.
- Thus, in addition to the fact that the latter is semi-distributed, this solution cannot be applied in the large scale networks since it may lead to a large delay, and can even lead to network congestion.

4.4/ Simulation results

In this stage of simulation, we use the same topology and parameters for the video sensors as in Section 3.7. In addition to these parameters, we set the transmission and reception maximal powers to $P_{t_{max}} = 2.63$ W and $P_{r_{max}} = 1.5$ W, respectively. The additive white Gaussian noise is set to $N_0 = 0.5$, while the bandwidth is set to $W = 2.4$ Ghz.

Table 4.4 shows the maximum number of bits that can be transmitted by each link (denoted by C_l in the fifth column in Mbps). The third and fourth columns represent the number of bits transmitted in the communication medium by each node. The third column, denoted by 1st.pr, presents our proposal in Section 3.6 (*i.e.*, without the link capacity constraint), and the fourth one, denoted by 2nd.pr, presents our proposal in Section 4.3 (*i.e.*, with the link capacity constraint).

Nodes	**Links**	x_{hl} **Mbps**(1st.pr)	x_{hl} **Mbps**(2nd.pr)	C_l **Mbps**
0	0	**0.1719**	0.063678	0.0637379
	1	0.007728	0.0644505	0.0648071
	2	0	0.0489836	0.0513569
1	3	0.008010	0.0596555	0.0642484
	4	0.0553	0.0609048	0.0609766
	5	**0.116339**	0.0566486	0.0636252
2	6	0	0.0475314	0.0475533
	7	**0.17962**	0.0671274	0.0689719
	8	0	0.0630749	0.0639375
3	9	0	0.0474827	0.0475048
	10	**0.18527**	0.0624015	0.0637154
	11	**0.096835**	0.0588299	0.05889103
	12	0	0.0438097	0.0438743
4	13	0	0.128369	0.129802
	14	**0.188237**	0.140891	0.141008
5	15	0	0.06101	0.0657074
	16	0	0.0550086	0.069987
	17	**0.179621**	0.0628223	0.0679477
6	18	**0.17952**	0.139564	0.1398876
7	19	**0.29441**	0.102801	0.105697
	20	0	0.098788	0.0988502
8	21	**0.179526**	0.141226	0.151849

We can observe that the 1st.pr exceeds the links capacity in the majority of cases: this is emphasized in bold in the table. On the opposite, the 2nd.pr totally respects the capacity of each link.

Figure 4.1 shows the convergence of our algorithm to a common variable q, and we can observe that, compared to the common variable q presented in figure 3.4, we have increased the network lifetime by 2.72 times (since $T_{net} = 1/q$). This effectiveness can be explained by the balanced distribution of the rates on the links.

Figure 4.2 shows the lifetime of each node, and here also we can observe that our proposal effectively maximizes the nodes lifetime, and thus the network lifetime. With respect to the lowest node lifetime (here node 3), we have increased the network lifetime by at least 8.21 times, since the latter had only $1.6393x10^6$ s of the remaining lifetime without considering the optimization steps. However, the activity duration was increased by approximately twice compared to the first solution.

Let us now study the network lifetime of the proposed distributed solution under the dynamic change of the links capacity. To ensure the effectiveness of our solution, we have also implemented the *DQLM* solution, proposed by authors in [49], in OMNET++ (using the same simulation bases as for our proposal), by using the topology in figure 4.3 (heavily borrowed from [49]).

4.4.1/ Energy cost

Figure 4.4 shows the requirement in term of battery spent to ensure an optimal power and rate allocation (*i.e.*, battery consumption requirement for the optimization step). In these results we have only considered the nodes with the highest battery consumption, namely, node3 for our proposed solution with dynamic change of links capacity, node1 for the *DQLM* solution and node5 for our proposed solution in Section 3.6 (without applying the links capacity).

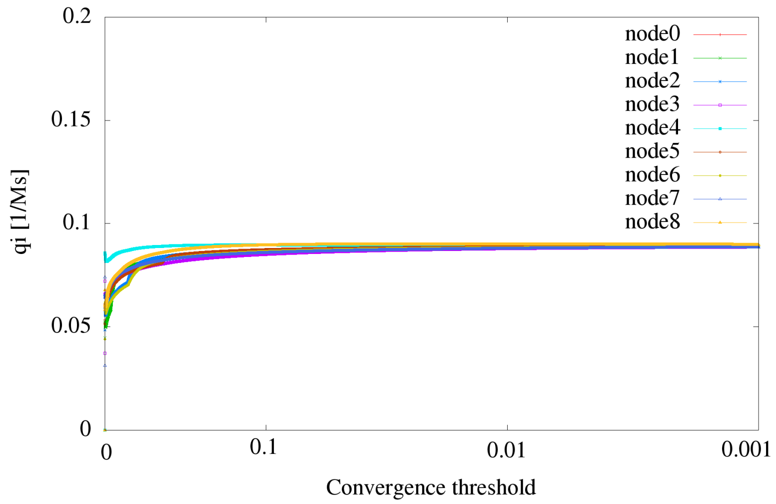

Fig. 4.1: Auxiliary variables convergence

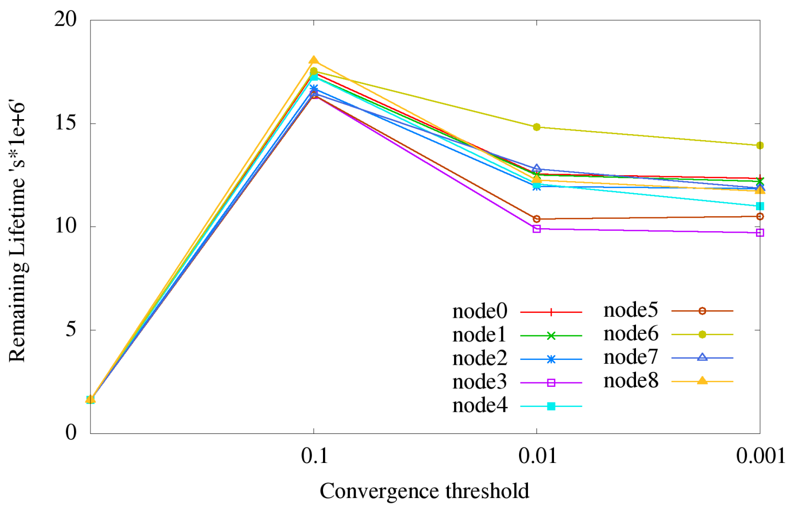

Fig. 4.2: Node Lifetime after each convergence threshold

We can observe that there is a minor difference between the solutions with/without applying the dynamic change of the links capacity (*i.e.*, proposed with c_l and proposed without c_l, respectively). To ensure the 10^{-2} convergence threshold, our proposed solution, with the dynamic change of links capacity, ensures the lesser battery consumption. However, it requires more iterations and thus more energy consumption to gain more precision (*i.e.*, convergence threshold $< 10^{-2}$) with respect to the common variable q, compared to the solution without c_l.

Regarding the *DQLM* solution, we can observe that there is a considerable difference in term of battery consumption compared to our proposed with dynamic change of links capacity. This difference can be explained by the fact that the *DQLM* solution is semi-distributed, while our solution is fully distributed. Therefore, our solution requires more time to converge, which explain the elevated requirement in term of energy, and thus the elevated battery requirement compared to *DQLM* (especially in such a topology, where there is a minor communication between the different sensor nodes).

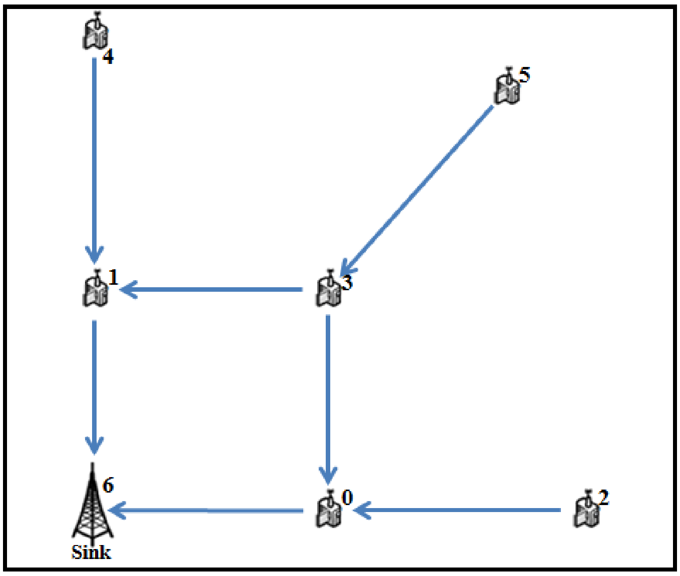

Fig. 4.3: Second Topology [49]

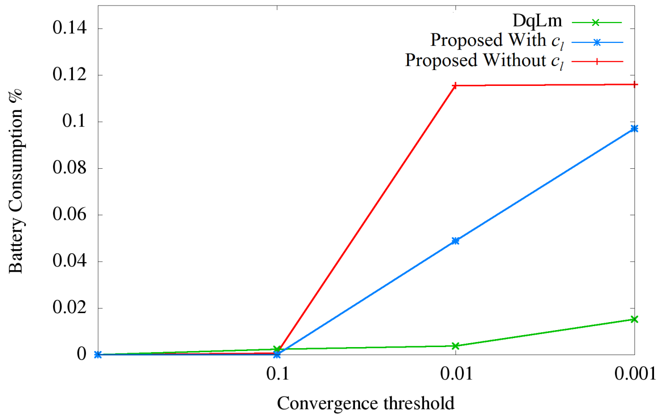

Fig. 4.4: Battery Consumption Comparison

4.4.2/ Network lifetime

Let us recall that the main objective of this chpater is to maximize the network lifetime, by finding the optimal power and rate trade-off, while ensuring the desired video quality at the destination (namely, the sink node). Thus, to calculate the network lifetime, we can simply inverse the q_i variable as described in Section 3.5.

Figure 4.5 shows that our approach maximizes the network lifetime by 4 times compared to the *DQLM* solution, and by 1.8 times compared to the first proposal (*i.e.*, without applying the links capacity), which demonstrates that the proposed design, with dynamic change of links capacity, efficiently increases the network lifetime.

In the above part, we have considered a dynamic change of the link's capacity and shown the effectiveness of the proposed solution. However, we have considered a lossless transmission channel. Note that, the wireless medium may be subject to different problems such that: interferences, link quality degradation, link failure, etc. Therefore, cope with

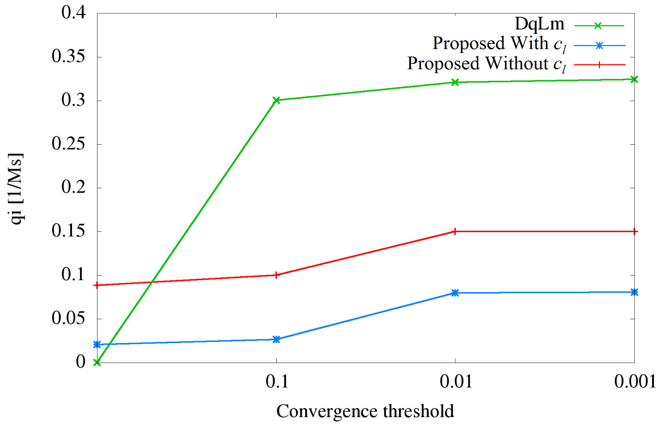

Fig. 4.5: Network lifetime inverse comparison

this kind of problems remains a challenging task. Thus, we will address this problem in the next section.

4.5/ Maximum network lifetime with lossy transmission channel

The wireless medium used by the video sensor nodes is inherently exposed to various sources of unreliability problems such as node failures, unreliable communication channels, transmission errors. The interferences caused by the density of the deployed sensor nodes my lead to a packet loss. Thus, the retransmission of lost packets can be used to recover such a problem. In the previous sections we have studied the maximum network lifetime using lossless channels. In this section, we investigate the additional energy requirement for the retransmission and its impact over the wireless video sensor network.

4.5.1/ Packet loss

To avoid the retransmission of a lost packet over all the intermediate nodes, we consider a negative acknowledgment to be sent back by the receiver to the sender if the packet was not correctly received. At the reception of such a request, the sender will retransmit the packet. Even though that the retransmission improves the video quality at the destination. However, it requires additional energy consumption, and thus, it reduces the network lifetime.

Let us now model the channel at each link using the two-state Markov Chain [46], in which the packet is considered as correctly received (resp. received with errors) if the channel is in the GOOD (resp. BAD) state. Taking into account the transitions: from a GOOD to the BAD state (denoted: $T_{GB}(l)$) and from a BAD to a GOOD state (denoted: $T_{BG}(l)$), the average bit error probability $P_{BE}(l)$ at link l is given by:

$$P_{BE}(l) = \frac{T_{GB}(l)}{T_{GB}(l) + T_{BG}(l)}. \tag{4.17}$$

Let S be the length in bits of the packet, and let $P_R(l)$ be the packet loss rate. It can be easily deduced that $P_R(l) > 0$ if and only if $S > 0$ (*i.e.*, there is a bit error in the packet). Thus, the $P_R(l)$ at the link l can be formulated as the following:

$$P_R(l) = 1 - (1 - P_{BE}(l))^S. \tag{4.18}$$

4.5.2/ Problem formulation and solution

Based on the previous formula and using the Markov channel error model, the average number of transmissions $\overline{n}$ required over each hop (*i.e.*, each link l) to ensure the successful receiving of a packet, can be expressed as the following:

$$\begin{aligned} \overline{n_l} &= (1 - P_R(l)) + 2P_R(l)(1 - P_R(l)) + 3(P_R(l))^2(1 - P_R(l)) + ... \\ &\simeq \frac{P_R(l)}{1 - P_R(l)}. \end{aligned} \tag{4.19}$$

Therefore, the total power consumption presented in (3.6) should be replaced by the following:

$$P_i = P_{sh} + \overline{n_l} P_{ti} + \overline{n_l} P_{ri} \quad \forall l \in \mathcal{L}, \forall i \in \mathcal{N}. \tag{4.20}$$

Note that, for simplification, we assume the successfully receiving of the negative acknowledgments sent by the destination nodes, and the negligible energy consumption to process and send such a packet.

Based on these assumptions, and taking into account the retransmission energy consumption, the network lifetime maximization problem formulated in (4.7), can be reformulated as follows:

$$\begin{aligned} &\underset{(q,x,R,P_s)}{\text{minimize}} \sum\nolimits_{i\in\mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_{h} R_h^2 + \delta_p \sum_{h} P_{sh}^{8/3} \\ &\text{subject to} \sum_{l\in\mathcal{L}} a_{il} x_{hl} = \eta_{hi} \quad \forall h \in \mathcal{V}\ \forall i \in \mathcal{N}, \\ &\qquad \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \leq D_h \quad \forall h \in \mathcal{V}, \\ &\qquad P_{sh} + \sum_{l\in L} a_{il}^{+} \overline{n_l} (c_l^s \sum_{h\in V} x_{hl}) \\ &\qquad + c^r \sum_{l\in L} a_{il}^{-} \overline{n_l} (\sum_{h\in V} x_{hl}) \leq q_i B_i, \quad \forall i \in \mathcal{N} \\ &\qquad \sum_{i\in\mathcal{N}} a_{il} q_i = 0 \quad \forall l \in \mathcal{L}, \\ &\qquad \sum_{h\in\mathcal{V}} x_{hl} \leq W \log_2 \sqrt{1 + \frac{P_{rl}}{N_0 W}} \quad \forall l \in \mathcal{L}, \\ &\qquad \sum_{l\in\mathcal{L}} a_{il}^{+} P_{t_l} \leq P_{t_{max}} \quad \forall i \in \mathcal{N}, \\ &\qquad \sum_{l\in\mathcal{L}} a_{il}^{-} P_{r_l} \leq P_{r_{max}} \quad \forall i \in \mathcal{N}, \\ &\qquad x_{hl} \geq 0, R_h \geq 0, P_{sh} > 0, q_i > 0. \end{aligned} \tag{4.21}$$

The problem constitutes a convex optimization problem with respect to all decision variables. Therefore, it can be solved by proceeding as in Section 4.3, using the primal-dual method.

4.5.3/ Simulation results

In this section we use the same topology and parameters initialization as in Section 4.1. To generate different values of $P_R(l)$, we chose to make the transition probability varying between $T_{GB}(l)$ and $T_{BG}(l)$.
Figure 4.6 shows the different level of battery consumption depending on the $P_R(l)$ value. We can observe that more is the number of the corrupted packet, more is the battery consumption required for the optimization step, and thus due to the re-transmission process.

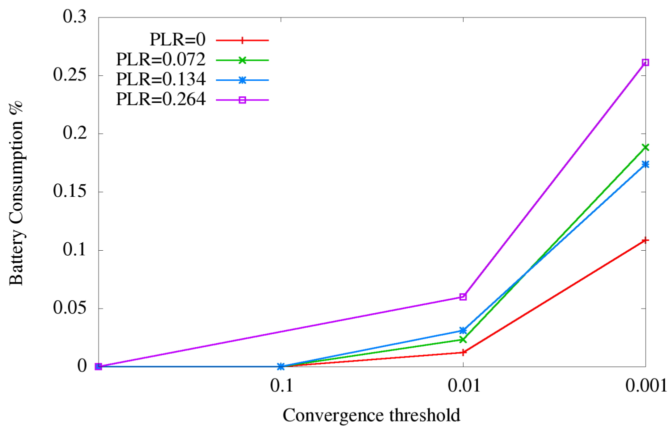

Fig. 4.6: Battery consumption with lossy transmission channel

Let us now focus on the network lifetime as shown in Figure 4.7. We can observe that compared to the lossless transmission (where $P_R(l)$ is equal to 0), the maximum network lifetime is reduced by increasing the $P_R(l)$ average. This reduction is by 6.27% when $P_R(l)$ is 7.2%, by 10.55% when $P_R(l)$ is 13.4%, and by 20.02% when $P_R(l)$ is 26.4%.

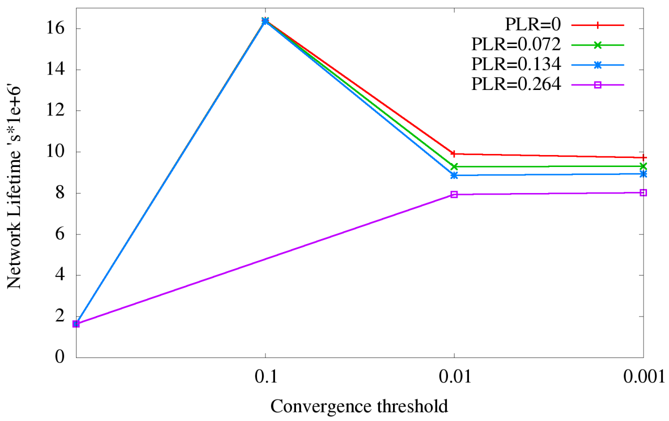

Fig. 4.7: Network lifetime with lossy transmission channel

4.6/ Conclusion

In this chapter, and after ensuring an optimal power/rate resource allocation that maximizes the network lifetime while respecting the desired video quality at the destination in the previous chapter, we have extended our proposal by allowing it to handle a **dynamic change of links capacity**. In other terms, we included additional constraints. To this end, a novel mathematical model was formulated considering both limited links capacity and limited transmission and reception powers. In order to evaluate the effectiveness of our proposal over state-of-the-art approaches, we have implemented, in addition to our approach, the one, named *DQLM* [49], using OMNET++ simulator. Simulation results show that our approach increases the network lifetime by 4 times compared to *DQLM* solution.

Furthermore, we have extended our proposal to handle the channel transmission error. The retransmission mechanism was used based on the two-state Markov Chain [46]. However, and as it was expected, the simulation results show that more is the packet loss rate, more is the requirement for data retransmission, and hence, lesser is the network lifetime.

After ensuring an optimal power/rate resource allocation that maximizes the network lifetime while respecting the desired video quality at the destination, the next chapter will tackle the second challenge of this thesis, namely, the data routing axis and how can the latter be combined with the data processing axis (that was already considered).

5

Routing impact on Network Lifetime Maximization using Power/Rate trade-off in WVSN

5.1/ Introduction

Previous research works have tackled the issue of finding a balance between the video data encoding *versus* the perceived video quality at the sink, by not considering the routing issue; *i.e.*, they consider that it has been done separately during the network initialization. In other term, routing is ”viewed” as a network input and not as a parameter to optimize. The purpose of this chapter is to demonstrate, through extensive simulations, the impact of the routing policy on the approaches used to find such a balance. To this end, we first considered several well-known routing approaches in WMSNs and extensively analyzed the impact of each one by considering three main parameters: battery consumption, activity duration, and network lifetime. The simulation results show clearly the great impact of the considered routing approaches on the obtained resource's consumption balance.

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5.2/ Network Assumptions

In this contribution, the same assumptions as those made in chapter 3.5, were kept (namely, the distance from the sink, the interferences, the routing matrix, the link capacity and the different transmission rates).

5.3/ Problem formulation

Note that, in this section we assume that the routing is completely pre-defined (*i.e.*, will not be integrated in the optimization steps), since the objective of this chapter is to analyze the impact of routing on the maximum achievable network lifetime. And thus, demonstrate the necessity to further integrate routing in the optimization problem.

Let us recall the problem formulation that will be used in this chapter:

$$\begin{aligned}
\underset{(q,x,R,P_s)}{\text{minimize}} \; & \sum\nolimits_{i\in\mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_h R_h^2 + \delta_p \sum_h P_{sh}^{8/3} \\
\text{subject to} \; & \sum_{l\in\mathcal{L}} a_{il}.x_{hl} = \eta_{hi}, \\
& \sigma^2 e^{\gamma.R_h.P_{sh}^{2/3}} \leq D_h, \\
& P_i \leq q_i.B_i, \\
& \sum_{i\in\mathcal{N}} a_{il}.q_i = 0, \\
& x_{hl} \geq 0, R_h \geq 0, P_{sh} > 0, q_i > 0.
\end{aligned} \tag{5.1}$$

The problem constitutes a convex optimization problem with respect to all decision variables [21], which can be solved by Primal-Dual method [93] as it has been detailed in chapter 3.

5.4/ Routing protocols

Routing is one of the most important design issues in WVSN. Therefore, several metrics should be taking into account in order to ensure an optimal propagation of data, namely, energy consumption, delay, bandwidth and video quality.

In this section, we recall the definition of the different well-known routing protocols to be used in the comparison via simulations in section 5.5:

- ***BroadcastRout***: Each node i in the network, except the sink, broadcasts the packet to all its neighboring nodes.
- ***ProbaRout***: Each node h chooses one node among its neighbors in an equitable manner, with a probability P set to $\frac{1}{Nbrs_h}$, where $Nbrs_h$ denotes the number of h's neighbors.
- ***GeomRout***: Each node h verifies at first if the sink is in its communication range. In the positive case, it sends the packet directly to the sink. Otherwise, it chooses the closest node to itself in the direction of the destination.
- ***ShortPathHop***: In this routing protocol, each node h selects the shortest path to the sink in term of number of hops. The chosen intermediate sensor node should be the farthest one (in the communication range of h), among the neighboring nodes of h, in the direction of the destination.
- ***ShortPathDist***: This strategy consists of choosing the shortest path to the destination in term of Euclidean distance (w.r.t. a given distance). Thus, the chosen candidate may be the nearest one, the farthest or even the one in between.
- ***MultiPathRout***: Each node h in the network, selects randomly two of its neighboring nodes to reach the destination. At the end, the sink should be chosen by at least two sensor nodes (those that they have it in the communication range) as one of their destination.

- ***ArbitraryRout***: This strategy is the one defined in our previous work (chapter 3 and chapter 4), and heavily borrowed from [54]. The objective was to send data over multi-paths toward the sink node, the intermediate nodes were chosen in an arbitrary manner.

5.5/ Simulation Results

In this section, we evaluate the impact of each of the aforementioned routing protocols, through extensive simulations. The routing protocols were implemented as an add on to the optimization problem presented in section 5.3 (*i.e.*, the routes and neighbors were computed separately before starting the data processing optimization steps), through MiXiM framework [71], using OMNET++ simulator [119].

In order to study the impact of routing on the network lifetime, two topologies were considred (Figure 5.1 depicts the configuration networks C_1 and C_2, respectively.), where the sink was placed in two different places, in the first configuration the sink was placed at the corner of the network, while for the second, the sink was placed in the middle of the network.

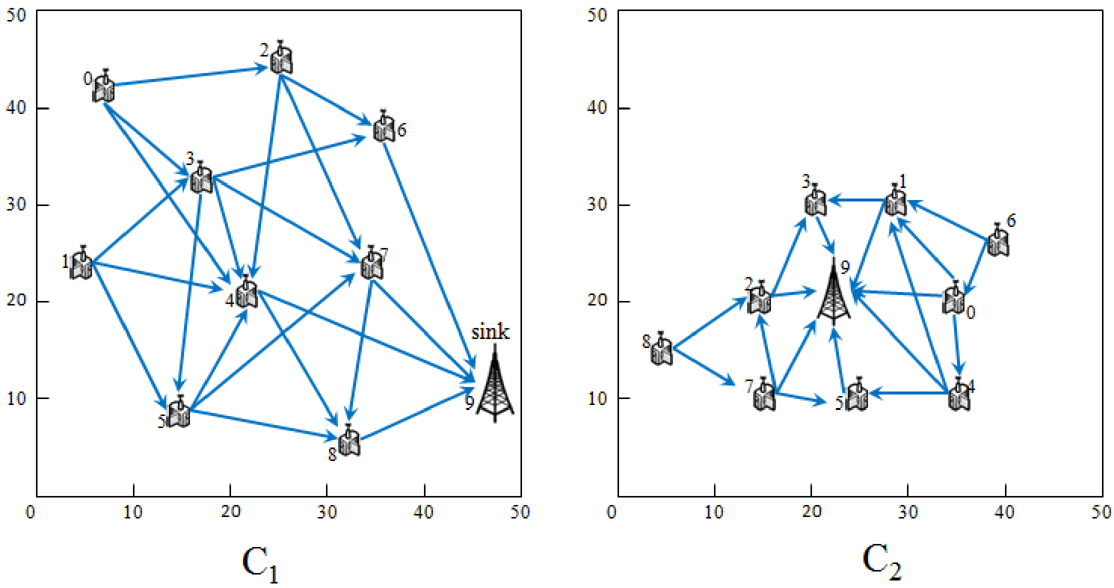


Fig. 5.1: Network configurations: C_1 C_2

One of the most critical issues in WMSN is to prolong the network lifetime. For this, it should be known that the two dominant operations that cause the network lifetime breakdown are: data transmission and video encoding (*i.e.*, video compression).

In this section we investigate the impact of data routing on a fully distributed system that provides a compromise between the encoding power and data rate.

First, let us recall that the distributed solution can be satisfied if and only if all the q_i $(i \in N)$ converge to a common variable q. In this work, we consider the system as completely stable when the maximum variation between the q_i $(i \in N)$ is 10^{-2}, in order to minimize energy consumption required for a system to gain more precision (with respect to q_i). Three fundamental parameters were studied and detailed in the following sections.

5.5.1/ Energy cost

Let us start by comparing the energy cost for each routing protocol. Figure 5.2 shows the battery consumption of the optimization steps for the two configurations C_1 and C_2, respectively. For the former configuration (Fig.5.2.(a)), we can see that at the 10^{-2} precision the *BroadcastRout* achieves the lowest battery consumption compared to author protocols, while the *ProbaRout* protocol presents the highest (1.215%) battery consumption. This can be explained by the fact that, even if the *BroadcastRout* protocol floods the network by packets, it takes much less iterations to converge. For the latter configuration, this figure (Fig.5.2.(b)) shows that the *ShortPathHop*, *ShortPathDist* and *GeomRout* act exactly the same way, and have the lowest battery consumption, while the *ProbaRout* strategy remains the most demanding in term of battery consumption, regarding the number of iterations required to achieve a precision convergence. The fact that the *ShortPathHop*, *ShortPathDist* and *GeomRout* have exactly the same level of battery consumption can be explained by the definition of this protocols, that choose the sink once the latter is in the coverage area of the selector node.

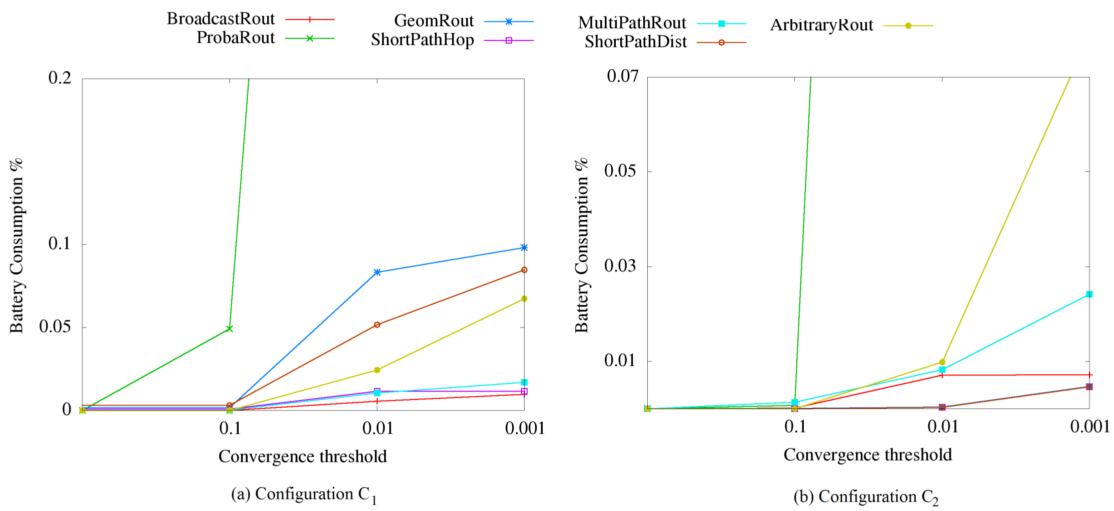
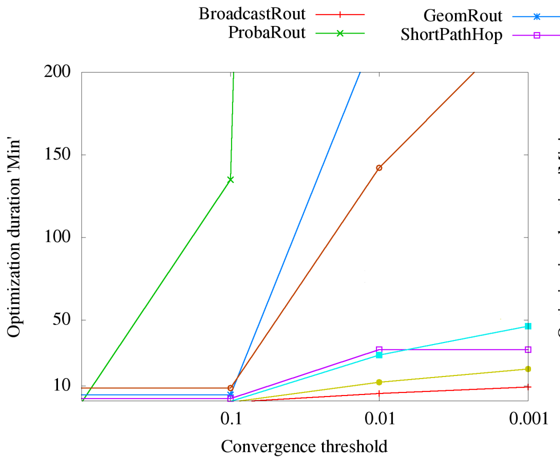


Fig. 5.2: Battery Consumption of optimization step

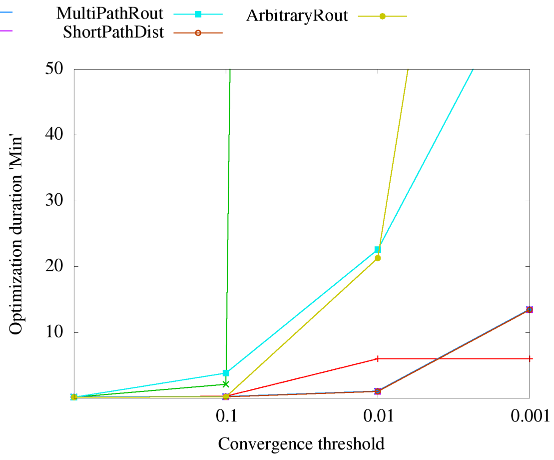
5.5.2/ Optimization duration

To make the network operational as soon as possible, one of the important elements to reduce is the time that the system takes to be functional. What is meant by *functional* is the termination of optimization steps. Thus, Figure 5.3 depicts the optimization duration for C_1 and C_2 configurations, respectively. First, we can see that with C_1 configuration, once we change the routing protocol, the optimization duration changes also and the difference is not the slightest. In Figure 5.3.(a), *BroadcastRout* protocol remains the most efficient and have the lowest optimization duration. Similarly, *ProbaRout* routing protocol remains the highest claimant in terms of optimization duration $(3333.479 Min)$. For the second configuration (*i.e.*, Figure 5.3.(b)), we can observe that the *ShortPathHop*, *ShortPathDist* and *GeomRout* have the lowest optimization duration. However, if more precision than 10^{-2} is required, the latter gives the way to the *BroadcastRout* strategy. The figure shows also that *ProbaRout* protocol have the biggest optimization duration to a value of 1755.19 minutes.

These differences, whether in the first or in the second configuration, is directly related to the required number of iterations to gain more precision (with respect to q_i).



(a) Configuration C_1



(b) Configuration C_2

Fig. 5.3: Activity duration

5.5.3/ Network lifetime comparison

Let us now focus on the main objective of this work, which is the study of the impact of the chosen intermediate nodes, for data routing, on the network lifetime. We first recall that in our context, we consider critical applications on which the depletion of only one node entails the depletion of the whole network. Figure 5.4 presents the improvement of the lowest node lifetime (that directly affects the whole network lifetime), in each routing protocol for the C_1 and C_2 configurations, respectively. The two subfigures show that contrary to the battery consumption and optimization duration parameters, here the *BroadcastRout* routing protocol presents the lowest improvement of node's lifetime with an improvement of 2.79 and 1.59 times in Figure 5.4.(a) and Figure 5.4.(b), respectively, compared to the initial node lifetime. This can be explained by the fact that, in this strategy, each node must not only broadcast its own data, but also broadcasts the multiple copies of the incoming data through its outgoing links. While the *ShortPathDist* for C_1 configuration augmented with *ShortPathHop* and *GeomRout* for C_2 configuration have the highest improvement of node's lifetime that was evaluated by 7.10 and 10.25 times, respectively, compared to the initial node lifetime. This can be explained by the fact that the Euclidean distance between each node and its destination affect the transmission power consumption and thus the node lifetime.

Let us now study the whole network lifetime. We remind that we have to minimize the inverse of the network lifetime, as recalled in section 5.3. Thus, the lowest the common variable q is, the longest the network lifetime is. Figure 5.5 depicts:

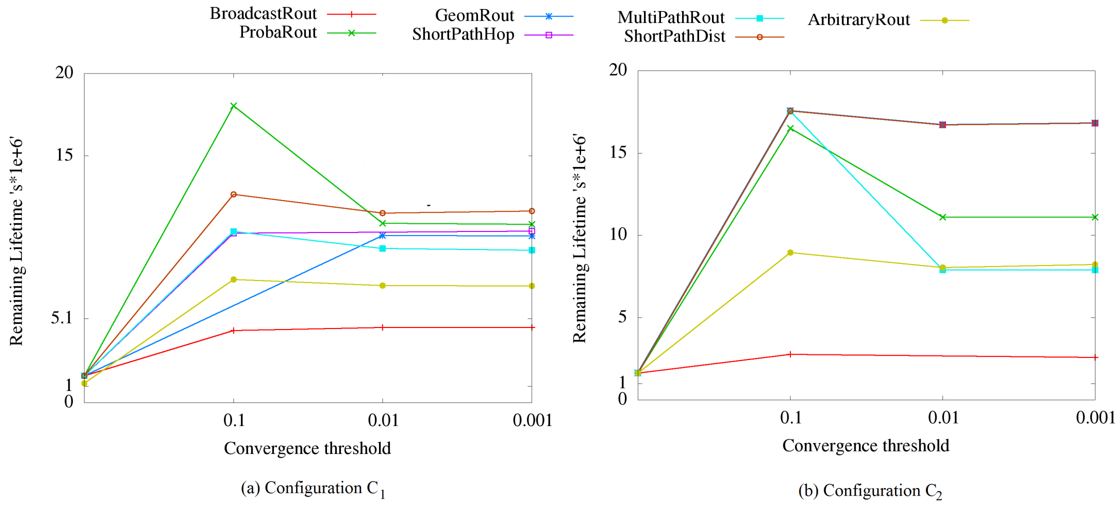


Fig. 5.4: Remaining Lifetime

- The convergence of the different routing protocols to a common variable q,
- and the whole network lifetime using each of these protocols.

For the C_1 configuration we can see that, from figure 5.5.(a), the *ProbaRout* protocol ensures the maximum network lifetime, while the *MultiPathRout* and *ArbitraryRout* have the lowest network lifetime, even compared to the *BroadcastRout* routing protocol. This slight difference can be explained by the fact that even if the *BroadcastRout* strategy floods the network by messages, this latter require much less iterations to converge to a common variable, allowing it to recover its huge requirement in term of transmission and reception power consumption. Contrariwise, in Figure 5.5.(b), *BroadcastRout* presents the lowest network lifetime, which was expected, as in the second configuration, almost all the nodes are in the coverage area of each other. While the *ShortPathDist*, *ShortPathHop* and *GeomRout* routing protocols ensure the maximum network lifetime, since they need only one path to reach their destination, namely, the sink.

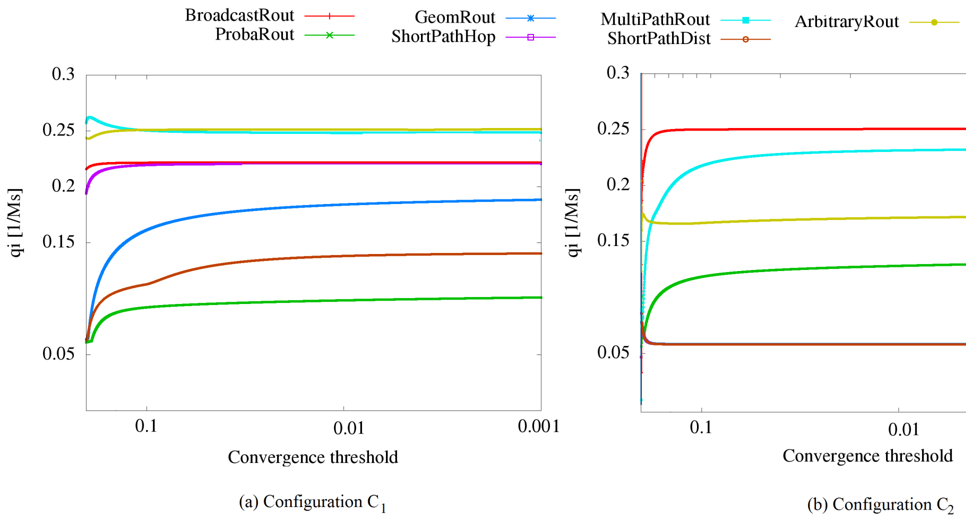


Fig. 5.5: Lifetime inverse $q = 1/T_{net}$

5.6/ Discussions

From the analyzes performed in the previous section, and based only on the first configuration C_1 figure 5.5.(a), we can easily say that the *ProbaRout* is the most appropriate routing protocol to transmit data in WVSNs, since the main objective is to maximize the network lifetime. However, taking into account the battery consumption and activity duration, this protocol presents the worst performance values. Note that, during the calculation of the battery consumption values we have also considered the real data transmission.

On the other hand, once the configuration changes, the results also change instantly, and the difference is not the slightest (as shown in Figure 5.5.(a) and Figure 5.5.(b)).

Although the choice of the routing protocol depends on the application requirements, we can conclude that the *ShortPathDist* and *GeomRout* present in average a good results in the both two configurations. More precisely, they present a good percentage of battery consumption and an acceptable activity duration while ensuring a good level of network lifetime maximization. However, the *ShortPathDist* protocol is more efficient in the first configuration.

5.7/ Conclusion

In this chapter, we evaluated through simulation several routing protocols in WVSNs, through two network configurations. All the routing protocols were implemented as an add on to a fully distributed solution presented in chapter 3, through MiXiM frame work, that was integrated in Omnet++ simulator. Simulations allowed us to compare the impact of each of these protocols on the network lifetime. In addition, the results have shown that, the choice of the forwarding nodes, affects enormously this latter.

For this reason the routing should be, without any doubt, considered and included in the optimization model to maximize the network lifetime. In the next chapter, we will integrate the routing optimization in an analytic model. Thus, we will solve such a new problem in a fully distributed manner.

6

Maximum Network Lifetime with Optimal Power/Rate and Routing trade-off for Wireless Video sensor Networks

6.1/ Introduction

In the previous chapter, we have demonstrated the impact of routing mechanism on finding a balance between the video encoding and the perceived visual quality at the sink. In this chapter, we focus then on the problem of simultaneously optimizing the video encoding at the source nodes and the routing of the generated data (*i.e.*, the routing matrix is initially unknown) to the sink in order to maximize the network lifetime. This issue is tackled through the proposition of an analytic model. Based on the latter, two solutions have been studied. In the first one, of a static nature (*i.e.*, network topology is static), the routes are calculated using the shortest path routing protocol toward the sink. This work has been published in 16th Wireless Communications and Networking Conference (IEEE WCNC), 2018.

Afterwards, in order to handle dynamic topology changes and to consider the link reliability, the work have been extended to the selection of routing paths, in a fully distributed fashion (*i.e.*, using a local decision hop-by-hop routing protocol) with respect to both the shortest ones and their reliability.

This work has been published in Computer Communications (COMCOM), 2018.

6.2/ The problem

In the previous chapter it was proved through simulation the highest network lifetime change, once the chosen routing protocol changes, which indicates that considerable lifetime values can be achieved. Thus, including the routing issue in our optimization problem leads to the following question: *what is the best way to select, among all available ones, the optimal routing path?* The "brute-force" approach consists in testing all the existing routing paths and then selecting the optimal one with regard to the lifetime metric. However, the number of possible routing paths can be very huge and testing all of them consumes time and energy. That is why was privileged *a heuristic approach*.

Let $\mathcal{P}_1$ be the problem of executing N routing protocols on a single instance of a network. Each routing protocol has an execution time denoted t_i. The main objective here is to find a scheduling that minimizes the positive number $L = \sum_{i=1}^{N} t_i$. This function tends to minimize the execution time of the routing protocols.

Theorem [1]. *The decision problem corresponding to the aforementioned problem is NP-complete.*

Proof 1. Let N be the number of routing protocols, with t_i the execution time of the routing protocol i, Et the time on which the routing protocol execution should terminate, and a positive number T. Is there a scheduling such as $L \leq T$?

- Given a solution, it is clear that the time taken to verify whether it is valid or not is $O(N)$.
- The problem, denoted by $\mathcal{P}_2$, that will be reduced to $\mathcal{P}_1$ is the *Knapsack problem*, which is defined as follows:

  A set $S = \{x_1, x_2, x_3, ..., x_n\}$ of n numbers and a positive number y such that: $\sum_{i=1}^{n} x_i = y$, is there $A \subset S$ such that: $\sum_{a_i \in A} x_i \leq y$?

Let us now construct the polynomial reduction f of the Knapsack problem to our $\mathcal{P}_1$ problem, in such a way that an instance I of the Knapsack problem, has a "yes" answer, if and only if $f(I)$, an instance of our problem, has a "yes" answer. Let I be an instance of Knapsack problem. An instance $f(I)$ of our problem can be formulated as follows:

- $N = n + 1$;
- $t_i = x_i$; $Et_i = \sum_{i=1}^{n} x_i + 1$; $i = 1, ..., n$
- $t_{n+1} = 1$; $Et_{n+1} = y + 1$.

We will prove now that $L \leq T$ if and only if there is a set A such that $\sum_{a_i \in A} x_i \leq y$. Suppose that the subset A such that $\sum_{a_i \in A} x_i \leq y$ exists. Then, consider a scheduling that executes first the subset A in an arbitrary order, then the $n + 1$ routing protocol, afterward the $S - A$ subset. The routing protocols in a subset A end at y in the worst cases, since $\sum_{a_i \in A} x_i \leq y$. The y routing protocol ends at $y + 1$, and the rest of the routing protocols end at $\sum_{i=1}^{n} x_i + 1$. Thus all routing protocols were executed and thus $L \leq T$.

It can be concluded that if the Knapsack problem has a solution then $\mathcal{P}_1$ also has a solution.

Suppose now that our problem $\mathcal{P}_1$ has a solution, thus it has to be proven that the Knapsack problem also has a solution. In order to prove this implication, it is simpler to show its contraposition. In other words, suppose that the Knapsack problem does not have a solution which implies that there is no solution $A \subset S$ such that $\sum_{a_i \in A} x_i \leq y$. Let A be the subset of the routing protocols executed before the $n + 1$ routing protocol, which implies that the execution of A ends at: $E_A = \sum_{a_i \in A} x_i > y$, by hypothesis. The $n + 1$ routing protocol will be executed after and ends at $E_A + 1$, and thus $L > T$.

Therefore, if the Knapsack problem has a negative response, then so does $\mathcal{P}_1$. The Knapsack problem is equivalent to our problem, and thus, it can be deduced that $\mathcal{P}_1$ is Np-complete. □

6.3/ Network Model with a Geographic progression

Let us consider a multimedia sensor network consisting of $\mathcal{N}$ identical stationary multimedia sensors. Each of which knows its coordinates, by means of any localization mechanism [16, 122], and the coordinate of the sink. Each node h has a communication range denoted *ComRange*, and generates a multimedia traffic of rate R_h to be sent to the sink.

Upon the network deployment, the neighboring table is constructed by the means of a *Hello message* broadcasted by each node. Using this step, each node can also record the coordinates of its immediate neighbors (used later for the geographic routing).

As a first step to our approaches, we consider the geographic progression of the generated data flow from source nodes toward the sink. This step allows to assign an orientation to each link in the network. In other works, this orientation follows the data traffic flow. The motivation behind doing so is to ”simplify” the data routing on the one hand and on the other hand to follow the video data flow which is voluminous. Figure 6.1 shows an example of a directed WVSNs composed of 9 sensor nodes and one sink deployed in a region of 50mx50m. This figure presents all the existing links between each node and its one-hop neighboring nodes. The orientation of each link has been set following the geographic progression to the sink.

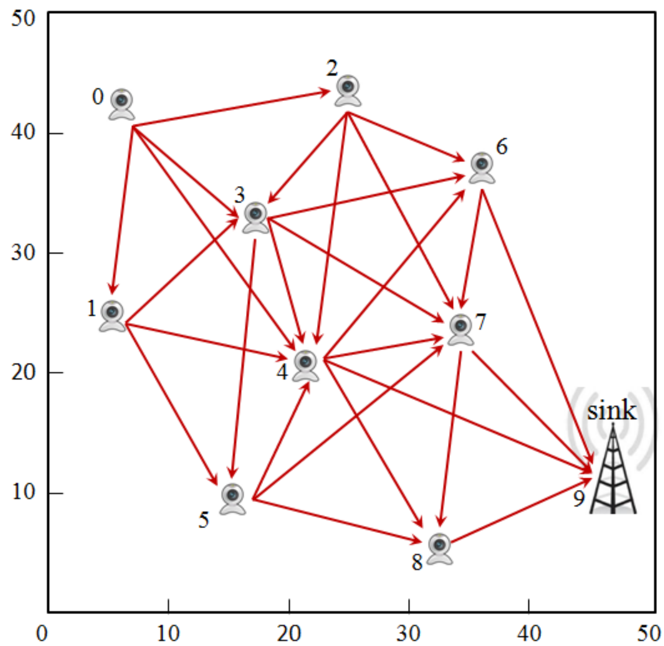


Fig. 6.1: Example of a WMSN.

6.4/ Routing constraints formulation

As previously mentioned, the interaction between the processing and the delivery of multimedia content has a major impact on the network lifetime. Thus, the video encoding and routing are complex tasks that consume energy and hence impact the overall energy of the network. In this section, we focus our interest on the data routing axis, in order to construct the adequate formulation that optimally chooses the next forwarding node. The developed formulation will be integrated into the analytical model in order to be combined with the data processing axis constraints.

6.4.1/ Shortest path routing protocols

In this subsection the aim is to minimize as much as possible the energy consumed by each node for data transmission. Based on the literature, the shortest path (*i.e.*, paths) represents the minimum-energy routing topology if data are not aggregated [27,28]. Thus, we briefly present the most knowing shortest path routing protocols in the following:

6.4.1.1/ Dijkstra's algorithm

Dijkstra's algorithm (DA) is known as a single-source shortest path. It computes the shortest path from the source node to each of the nodes in the network. To find the shortest path, the Dijkstra algorithm works as follows:

- To start the DA assign distance of the source node to 0 and infinity for all the other nodes.
- In order to cope with loops, the DA marks the current node as visited.
- Then, it calculates a new distance for the all the neighbors of the current node by adding the distance of the current node and the link weight of the neighbor (if the new distance is smaller than the current value the DA updates the distance).
- The DA repeats the this steps (from the second step) until reaching the destination node.

6.4.1.2/ Bellman-Ford algorithm

As Dijkstra algorithm, Bellman-Ford (BFA) algorithm is also known as a single-source shortest path. But, different from DA, BFA is based on the relaxation method. This method takes into account two nodes (initial source node and final destination nodes) and the link connecting these nodes. The distance, from the initial source node to the first intermediate node, is held if the latter is the smallest between all the existing neighboring nodes distances, and the first node is denoted as the predecessor of the other existing intermediate nodes. Then, the distance to these latter is recalculated.

6.4.1.3/ Floyd-Warshall algorithm

Unlike Dijkstra and Bellman-Ford algorithms that find a shortest path from one node to all nodes, Floyd-Warshall algorithm (FWA) finds a shortest path between all the pairs of the network. To find the shortest path, the FWA algorithm works as follows:

- Firstly an adjacency matrix is initialized giving the weight of an arc if it exists and infinity otherwise.

- The distance between the given source node and all the existing nodes is computed by comparing the distance of all the existing paths using the matrix.

- The shortest path is held and the algorithm is recalculated for the next node.

It should be noted that this algorithm does not return details of the paths.

6.4.1.4/ Discussion

To start, let us discuss the Floyd-Warshall algorithm that finds a shortest path between all the pairs of the network. This algorithm is not useful in our case due to the fact that we need to compute a shortest path (s) from the initial source to the final destination. Thus, it is useless to compute the shortest path between all the intermediate nodes even those that will not participate at the data forwarding.

Concerning the Dijkstra and Bellman–Ford algorithms, the Dijkstra algorithm is a greedy algorithm that efficiently selects the minimum-weight node, and thus, the shortest path to the destination. However, this latter needs the database of whole network and thus can not be efficiently brought to our network where the nodes are assumed to know only their one hop neighboring nodes. In contrast, the Bellman–Ford algorithm is a dynamic algorithm that simply relaxes all the edges and only requires local information.

For this reason, the distributed Bellman Ford algorithm was implemented with a slight adaptations that will be explained in the next section.

The distributed Bellman Ford approach has the following formulation [17]:

$$\mathcal{D}_i = \min_j [d_{ij} + \mathcal{D}_j] \tag{6.1}$$

where $\mathcal{D}_i$ is the shortest Euclidean distance from node i to the destination and d_{ij} is the Euclidean distance from node i to j (j is a one-hop neighbor of i, denoted by $Nbrs_i$). The inclusion of the minimum in (6.1) means that the best neighbor is selected to be included to the list of the shortest paths from i to the destination.

6.4.2/ Disjoint Paths

The benefits of disjoint paths routing are significant for high data multimedia applications [106]. It can be used to split the high data over the existing paths or even to cope with the links' failure. However, the disjoint paths problem is known to be NP-complete in directed graphs even if the number of disjoint paths is equal to 2. In this paper, two routing protocols are proposed with 2 and 3 paths, respectively, based on the Bellman Ford method.
The problem of the disjoint paths [64] can be defined as follows:
Given a directed network $G = (\mathcal{N}, \mathcal{L})$ of $\mathcal{N}$ nodes and $\mathcal{L}$ weighted links. Find k paths $p_1, p_2, ..., p_k$ from $i \in \mathcal{N}$ to the sink node, such that the paths share minimal common links (or nodes).

6.5/ Power/Rate and Routing Optimization

6.5.1/ Problem formulation

As previously mentioned, we aim to integrate the routing problem into the analytic model proposed in chapter 3 section 3.6 that ensures a trade-off between the desirable visual quality at the sink and the available network's resources.

Before going further, let us briefly recall the analytical model proposed in chapter 3 section 3.6.

$$\begin{aligned}
\underset{(q,r,x,P_s)}{\text{minimize}} \; & \sum_{i\in N} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_{h} R_h^2 + \delta_p \sum_{h} P_{sh}^{8/3} \\
\text{subject to} \; & \sum_{l\in\mathcal{L}} a_{il} x_{hl} = \eta_{hi} \quad \forall h \in \mathcal{V}\ \forall i \in \mathcal{N}, \\
& \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \leq D_h \quad \forall h \in \mathcal{V}, \\
& P_{sh} + P_{ti} + P_{ri} \leq q_i B_i \quad \forall i \in \mathcal{N}, \\
& \sum_{i\in\mathcal{N}} a_{il} q_i = 0 \quad \forall l \in \mathcal{L}, \\
& x_{hl} \geq 0, R_h \geq 0, P_{sh} > 0.
\end{aligned} \tag{6.2}$$

Let us now introduce the routing constraints to (6.2):

$$\begin{aligned}
\underset{(q,r,x,P_s)}{\text{minimize}} \; & \sum_{i\in N} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_{h} R_h^2 + \delta_p \sum_{h} P_{sh}^{8/3} \\
\text{subject to} \; & \\
& 1)\ \sum_{l\in\mathcal{L}} a_{il} x_{hl} = \eta_{hi} \quad \forall h \in \mathcal{V}\ \forall i \in \mathcal{N}, \\
& 2)\ \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \leq D_h \quad \forall h \in \mathcal{V}, \\
& 3)\ P_{sh} + P_{ti} + P_{ri} \leq q_i B_i \quad \forall i \in \mathcal{N}, \\
& 4)\ \sum_{i\in\mathcal{N}} a_{il} q_i = 0 \quad \forall l \in \mathcal{L}, \\
& 5)\ \mathcal{D}_i = \min_j [d_{ij} + \mathcal{D}_j] \quad \forall i \in \mathcal{N}\ \forall j \in Nbrs_i \\
& 6)\ a_{il}^+ = \{0, 1\} \quad \forall i \in \mathcal{N}\ \forall l \in \mathcal{L}, \\
& 7)\ a_{il}^- = \{0, 1\} \quad \forall i \in \mathcal{N}\ \forall l \in \mathcal{L}, \\
& 8)\ x_{hl} \geq 0, R_h \geq 0, P_{sh} > 0
\end{aligned} \tag{6.3}$$

The fifth constraint presents the shortest path from i to the destination going through the best neighbor. The sixth and seventh constraints present the indicators of the sender and the receiver, respectively.

One can ask, what about the power spent for neighboring discovery? The neighboring nodes discovery can be summed up in sending and receiving the "HELLO" message. Thus, the power spent for this discovery is also included in the transmission and reception powers computation (constraint 3). It should be noted that, the transmission and reception powers computation considers not only the delivery of real data, but also the communication of the optimization step parameters between the different nodes of the network, as well as any other exchange between nodes.

6.5.2/ PROBLEM RESOLUTION

In this section we present the resolution of Problem (6.3). Due to the rich structure of this problem, a decomposition approach can be applied in order to split the latter into a set of small subproblems. Thus, these latter can be solved in a distributed manner and converge to the global optimum [93]. Firstly, a primal decomposition with respect to the coupling variables (a_{il}^{+}, a_{il}^{-}) is required. Then, the dual problem can be formulated with respect to the coupling constraints (1), (2), (3) and (4). Finally, the original optimization problem (6.3) can be decomposed into two subproblems as follows:

$$\begin{aligned}
&\textbf{P1:}\min_{(q,r,x,P_s)} \sum_{i\in N} q_i^2 + \delta_x \sum_{h,l} x_{hl}^{\alpha_x} + \delta_r \sum_{h} R_h^{\alpha_r} + \delta_p \sum_{h} P_{sh}^{\alpha_p} \\
&\text{subject to } (1), (2), (3), (4), (8). \\
&\textbf{P2:}\min_{(a_{il}^{+}, a_{il}^{-})} U^{*}(a_{il}^{+}, a_{il}^{-}) \\
&\text{subject to } (5), (6), (7).
\end{aligned} \tag{6.4}$$

Note that the optimization of the **P1** problem is achieved if and only if the coupling variables (a_{il}^{+}, a_{il}^{-}) are fixed. Since, (a_{il}^{+}, a_{il}^{-}) are updated through **P2**, $U^{*}(a_{il}^{+}, a_{il}^{-})$ can be viewed as the optimal value for the **P1** problem and used to provide an approximation to the global optimal solution.

6.5.2.1/ P2 RESOLUTION

Next, the way to update the coupling variable (a_{il}^{+}, a_{il}^{-}) is discussed, based on the distributed Bellman Ford method, to solve the **P2** problem. The path (paths) discovery steps is executed according to the following steps:

Neighboring discover In this phase each video sensor node $i \in \mathcal{V}$ broadcasts a HELLO message in order to have the geographic coordination of its neighbors, and updates its neighboring table. At the end of this phase, each node i will have the routing matrices of its outgoing and incoming links (*i.e.*, a_{il}^{+} and a_{il}^{-}, respectively), as well as the routing matrices of the outgoing and incoming links of its one-hop neighbors $j \in$ *Nbrs*$_i$ (*i.e.*, a_{jl}^{+} and a_{jl}^{-}, respectively).

Path establishment After the neighboring discovery phase, each sensor node i initiates the Bellman Ford algorithm by sending $d_{ij} + \mathcal{D}_i$, where $\mathcal{D}_i = 0$ if i is the source and $\mathcal{D}_i = \infty$ otherwise. At the reception of such a message each node $j \in$ *Nbrs*$_i$ checks if $\mathcal{D}_j > d_{ij} + \mathcal{D}_i$. If it returns true j proceeds as follows:

- Set $\mathcal{D}_j = d_{ij} + \mathcal{D}_i$,
- marks the sensor node i as the best current predecessor,

- sends the estimate $d_{jk} + \mathcal{D}_j$ to each sensor node $k \in$ *Nbrs*$_j$,
- the operation continues until the sink node.

Path confirmation At the end of the path establishment step, the sink node should maintain the shortest Euclidean distance from each node to the latter as well as the latest node through which it has received this distance. Then, in the path confirmation phase the sink node sends a *pathConf* message through the inverse path.

Disjoint Path In order to construct multi-paths, the sink node instead of maintaining only the shortest Euclidean distance from each node to the latter, maintains the two or three shortest Euclidean distances paths.

Let us recall that the intermediate nodes have to send not only their own data, but also the data of their incoming neighbors which has a direct impact on their energy consumption and hence on the network lifetime. Thus, the main goal behind the use of disjoint paths is to balance the network load over the intermediate nodes. In other terms, the generated data from node h will be divided on the existing outgoing neighbors. Now, let us suppose that we will not ensure the disjoint paths, figure 6.2 can expose one of the undesired cases:

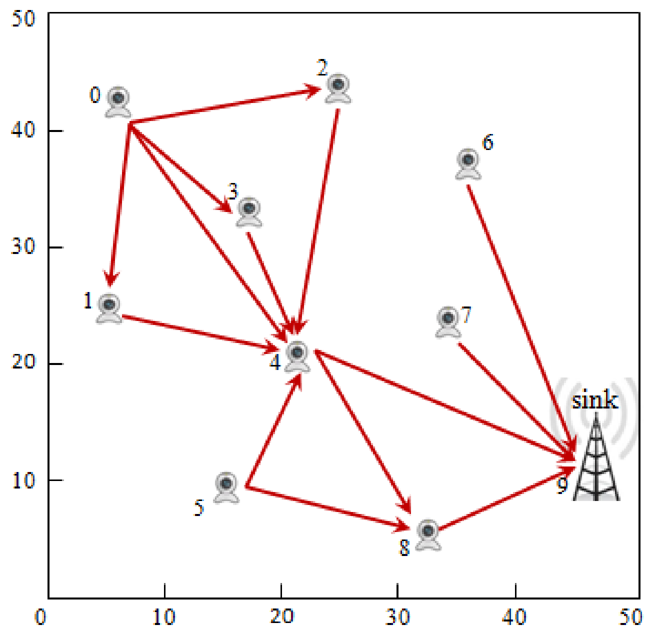


Fig. 6.2: Network with shared node

Our solution is fully distributed and each node only has the vision of its one hop neighboring. From figure 6.2, node 0 sends its own traffic to its neighboring nodes assuming that it has 4 paths, except that all the traffic will end up in node 4. This type of situation can rapidly bring down the energy of the intermediate node and affect the whole network lifetime.

Thus, to ensure a disjoint paths and avoid to have paths with a shared node, each node is limited into accepting only one message from an intermediate node with a given sequence number. Thus, node that receives more than one message, maintains the one with the minimum cost and ignores the rest.

6.5.2.2/ P1 RESOLUTION

The **P1** problem is solved as in chapter 3 section 3.6 using the Lagrangian Dual based methods [93].

6.6/ SIMULATION RESULTS

In this section, our routing/power-rate tradeoff approach is evaluated, through simulation. The model was implemented using OMNET++ simulator [119], through MiXiM framework [71]. As in chapter 3, the choice fell on the visual sensor settings of the *Panoptes* taking into account the similarities between the services provided by these latter and the target monitoring and surveillance visual application requirements. The same parameters initialization values of the video sensors presented in chapter 3, section 3.7, table 3.1, have been used in this section.

6.6.1/ CONVERGENCE OF THE PROPOSED SOLUTION

The convergence of the auxiliary variable q_i to a common q, can be observed in figure 6.3, where after a 10^{-2} convergence threshold, the system is seen to be almost stable. Thus, in the following, the system is considered as completely stable when the maximum variation between the q_i is $T = 10^{-2}$.

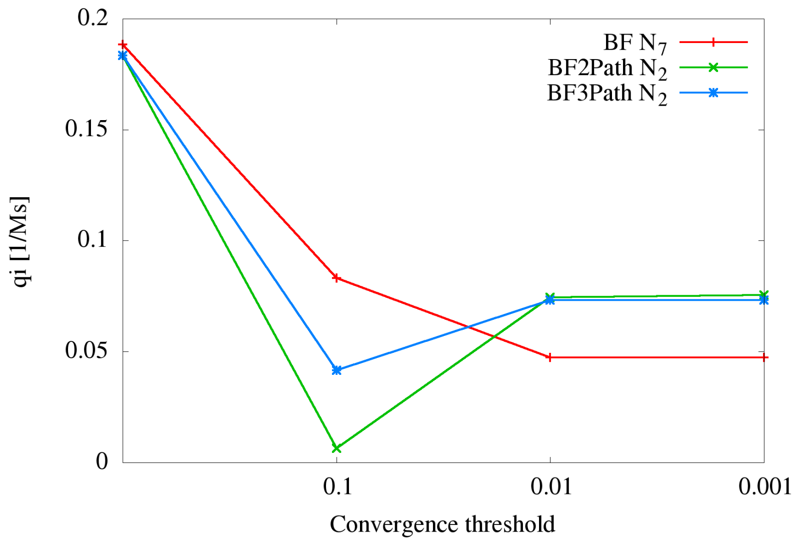


Fig. 6.3: Auxiliary variables

For the **P2** optimization, Table 6.1 shows the activity duration in seconds to find the optimal value of the coupling variables.

Table 6.1: Activity duration of the **P2** optimization

Routing protocol	Time (s)
Bellman Ford one path	5.35
Bellman Ford two paths	6.59
Bellman Ford three paths	7.19

6.6.2/ Optimization cost

In this subsection the cost of the optimization steps is analyzed, as both energy and duration at each node are considred.

6.6.2.1/ Energy cost

Figure 6.9 depicts the percentage of battery consumption of sensor nodes which consume the most, namely, node 7, node 2 and node 2 for one path, two paths and three paths, respectively. Thus, it concerns the total energy requirement for the optimization steps of both **P1** and **P2**. it can be observed that the routing protocol with only two paths (BF2PATH N_2) is the least energy applicant routing protocol. This observation can be explained by the fact that the one path routing protocol (BF N_7) requires much more iterations to converge and thus, it can get to the point of consuming more energy. Despite this, we can conclude that the optimization steps including both **P1** and **P2** consume a negligible amount of energy.

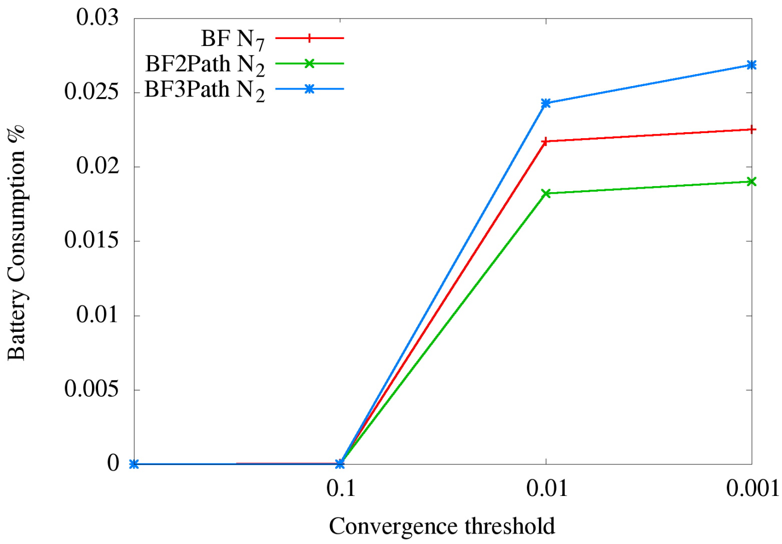


Fig. 6.4: battery consumption of optimization steps

6.6.2.2/ Optimization steps duration

At this stage of evaluation, we present the need in term of duration (in minutes) of the optimization steps to converge to the common variable q. Figure 6.10 presents the optimization steps duration including both: **P1** plus **P2**, for each threshold $T \geq 10^{-3}$ of the last converging nodes (namely, node 7, node 2 and node 2 for one path, two paths and three, respectively). It can be observed that, if more precision is required (*i.e.*, $T \geq 10^{-3}$, which depends on the demand of a given application), the system would need more time to be considered as completely functional (*i.e.*, all nodes converge to a common variable q).

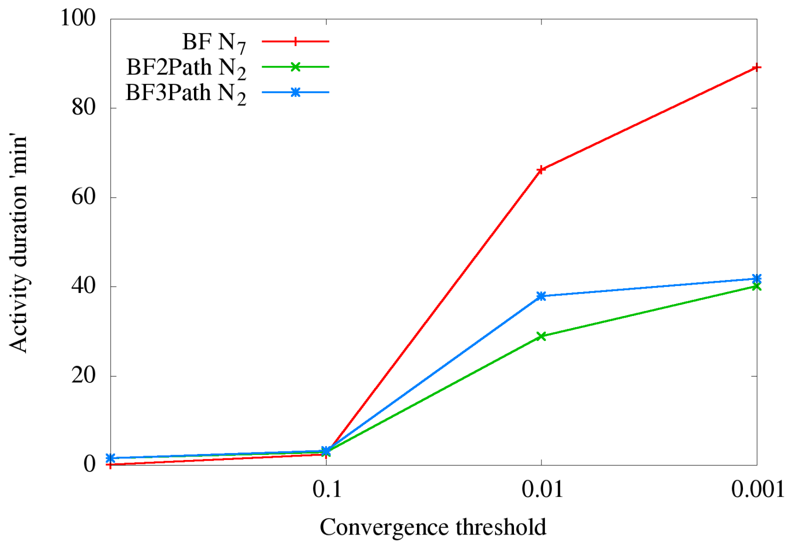


Fig. 6.5: Optimization duration

6.6.3/ Node lifetime improvement

The node lifetime can be calculated using the following formula: $T_i = B_i/P_i$.

Figure 6.6 shows the lowest improvement of nodes lifetime. it can be observed that with our optimization steps, and by including the routing constraints in the analytical model while imposing a trade-off between P_{sh} and R_h, the network lifetime has been increased by at least 7.72, 12.53 and 11.95 times considering the minimum nodes lifetime (*i.e.*, node 7, node 2 and node 2 for one path, two paths and three paths, respectively). It can also be observed that routing protocols with two paths (BF2PATH N_2) and three paths (BF3PATH N_2) ensure more network lifetime, since the multimedia content is distributed over the existing outgoing links. And thus, it demonstrates that the proposed design effectively increases the nodes lifetime and thus the network lifetime.

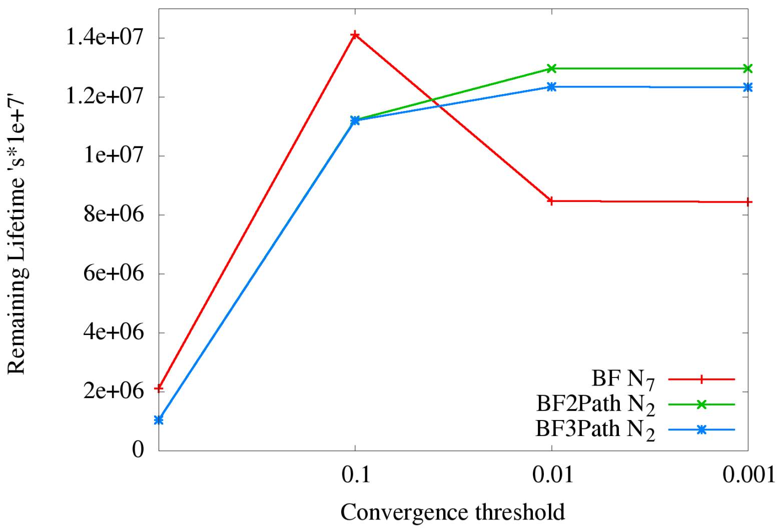


Fig. 6.6: Remaining lifetime after each convergence threshold

6.7/ Maximum Network Lifetime with reliability and Energy Aware Routing

It should be noted that the main problems in wireless multimedia sensor networks have been treated and separated mainly into two axes: **a)** the data processing axis and **b)** the routing axis. In the data processing axis the main objective is the optimal resource allocation (namely, the determination of the encoding power at the source level, and the video quality at the destination level). On the other hand, the main objective of the second axis (namely, the routing axis) is to find the optimal end-to-end path. However, treating each axis separately means that each axis ignores the parameters of the second one, which can lead to inefficient solutions.

To cope with this problem, we have proposed in the previous experimentation an analytical model (6.3) that takes as constraints the parameters of both data processing axis and data routing axis. Even if the problem was divided into two sub problems (namely, **P1** and **P2**), **P1** (*i.e.*, data processing problem) cannot be achieved without the results of **P2**. Nevertheless, it can be observed that the resolution of the **P2** problem (*i.e.*, routing problem) did not consider any of the parameters of the first one.

Therefore, in this section, we extend our study and propose a fully distributed solution that respects both the optimal resource allocation and the reliable end-to-end delivery of multimedia data content. In order to maximize the network lifetime, the routing axis goal cannot be achieved without the data rate and links capacity parameters, determined and updated by the data processing axis. On the other hand, the data processing axis goal cannot be achieved without the routing tables updated by the routing axis.

6.7.1/ Analytical model with multirate links

Before going further, let us first briefly discuss the novel analytic model used in the rest of this chapter. In contrast with the optimization problem (6.2) in section 6.5.1, a new model was chosen with more constraints (heavily borrowed from chapter 4, section 4.3) such as the dynamic links capacity and the limited power of both the transmission and reception processes, as shown in the following formulation:

$$
\begin{aligned}
\underset{(q,R,x,P_s)}{\text{minimize}} \; & \sum\nolimits_{i\in\mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_{h} R_h^2 + \delta_p \sum_{h} P_{sh}^{8/3} \\
\text{subject to} \; & \sum_{l\in\mathcal{L}} a_{il} x_{hl} = \eta_{hi} \quad \forall h \in \mathcal{V}\; \forall i \in \mathcal{N}, \\
& \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \le D_h \quad \forall h \in \mathcal{V}, \\
& P_{sh} + P_{ti} + P_{ri} \le q_i B_i \quad \forall i \in \mathcal{N}, \\
& \sum_{i\in\mathcal{N}} a_{il} q_i = 0 \quad \forall l \in \mathcal{L}, \\
& \sum_{h\in\mathcal{V}} x_{hl} \le W \log_2 \sqrt{1 + \frac{P_{rl}}{N_0 W}} \quad \forall l \in \mathcal{L}, \\
& \sum_{l\in\mathcal{L}} a_{il}^{+} P_{t_l} \le P_{t_{max}} \quad \forall i \in \mathcal{N}, \\
& \sum_{l\in\mathcal{L}} a_{il}^{-} P_{r_l} \le P_{r_{max}} \quad \forall i \in \mathcal{N}, \\
& x_{hl} \ge 0, R_h \ge 0, P_{sh} > 0, q_i > 0,
\end{aligned}
\tag{6.5}
$$

where, the Fifth constraint ensures that each data rate sent on each link respects the maximum link capacity. The Sixth and Seventh constraints ensure the respect of the maximum transmission and reception power, respectively, by each node.

6.7.2/ Distributed energy aware routing

As previously mentioned, each video node knows its own coordinates as well as those of the sink node, while the coordinates of its one hop neighbors are obtained through the execution of a *Hello* protocol. In order to minimize as much as possible the energy consumption at each node, and to ensure a fully distributed solution needed during the scale up of the network, we consider a hop-by-hop routing, rather than the traditional end-to-end path discovery routing and maintenance. The latter gives the ability for a video source node to control precisely a route so as to optimize a particular service goal (*e.g.*, reliability, bandwidth, energy consumption).

The proposed solution exploits the geographic locations to make a local decision at each video sensor node. The latter ensures a selection of the best downstream node(s) to be included to the list of the shortest path toward the sink node.

Let us give an example of such a selection: we consider the topology presented in figure 6.1. For node 5 the best neighboring node that ensures the shortest path to the sink is node 8. However, the latter may not respect the reliability requirement (for instance, the reliability of the link from 5 to 8 may be too small compared to the application reliability requirement). Thus, it could not be chosen. Therefore, node 5 chooses its second best neighboring node (*i.e.*, node 7) that ensures both: the second shortest path to the sink and respects the reliability requirement.

The main reasons behind such a choice are: **a)** the possibility of scalability to large scale video sensor networks, **b)** the maximization of the network lifetime and **c)** the possibility to handle with dynamic topologies. Thus, in solution to our problem, each node $i \in \mathcal{N}$ selects its downstream node(s) using the following formula:

$$dist(i, \mathcal{S}) = \min_{j \in Nbrs_i} [dist(i, j) + dist(j, \mathcal{S}) \mid dist(i, \mathcal{S}) \geq dist(j, \mathcal{S})] \tag{6.6}$$

where $\mathcal{S}$ is the sink node, and $dist(i, j)$ presents the Euclidean distance from node i to node j. Firstly, this formulation (6.6) ensures that the chosen node j, $j \in Nbrs_i$, gives a geographic progress toward the sink node ($dist(i, \mathcal{S}) \geq dist(j, \mathcal{S})$). Secondly, it ensures that the best downstream node is chosen (according to: $\min_{j \in Nbrs_i} [dist(i, j) + dist(j, \mathcal{S})$) and to be included in the list of the shortest path toward the sink.

Unlike the Bellman Ford formulation (6.1) presented in section 6.4.1.2, where the sink decides about the routes that each video node should take, here each node chooses its best downstream node based on its local information, and those of its one hop neighboring node (s).

6.7.3/ Link reliability

Due to the hard characteristics of the wireless medium (such as: the interferences, the link quality degradation, the link failure, or even the dynamic network topology, the node mobility, and the congestion), reliable multimedia content transmission in wireless video sensor networks is a challenging task. Thus, selecting the most appropriate downstream nodes toward the sink node is one of the main objective in this chapter.

Reliability is defined as the ratio of the successfully received packets ($SucRx$) by the destination at the link l, to the number of packets generated and transmitted (Tx) by source node at the same link l. Thus, for a given link $l \in \mathcal{L}$, the reliability $\mathcal{R}_l$ can be computed as follows:

$$\mathcal{R}_l = \frac{a^-_{jl} SucRx_j}{a^+_{il} Tx_i} \quad \forall j \in Nbrs_i \tag{6.7}$$

The latter should respect the link reliability defined by the application layer, denoted $RequiredReliability_l$ in the rest of this paper, as follows:

$$\mathcal{R}_l \geq RequiredReliability_l \quad \forall l \in \mathcal{L}. \tag{6.8}$$

6.7.4/ Traffic distribution

In our proposed solution, the path(s) is selected based on both the energy consumed in the data transmission process and the reliability required by the application layer. After the efficient selection of the intermediate node(s), another important issue that should be treated is the adequate number of paths that should be considered in order to achieve the performance demands of the target application. Therefore, we propose an additional path selection mechanism to choose the sufficient number of paths to provide reliable data transmission and traffic distribution.

The proposed mechanism is based on the traffic generated at each video sensor node R_h, $\forall h \in \mathcal{V}$, and the capacity of the channel C_l at each link l (Shannon's theorem (1984) [116]), and can be achieved as follows:

If $R_h \leq \sum_{l \in \mathcal{L}} a^+_{il} C_l$, $\forall i \in \mathcal{N}$ $\forall h \in \mathcal{V}$, then the number of the selected path(s) is sufficient. Otherwise, another path should be selected based on (6.6) and (6.7).

Once a set of paths is selected, the protocol distributes the network traffic over the selected paths with respect to the link capacity C_l.

6.8/ Problem formulation and resolution

In order to consider the parameters of both axes, the aim is to integrate the routing problem into the analytic model presented in (6.5). Thus, the final optimization problem can be formulated as the following:

$$
\begin{aligned}
\underset{(q,R,x,P_s)}{\text{minimize}} \quad & \sum\nolimits_{i \in \mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_h R_h^2 + \delta_p \sum_h P_{sh}^{8/3} \\
\text{subject to: } & 1) \ \sum_{l \in \mathcal{L}} a_{il} x_{hl} = \eta_{hi} \quad \forall h \in \mathcal{V} \ \forall i \in \mathcal{N}, \\
& 2) \ \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \leq D_h \quad \forall h \in \mathcal{V}, \\
& 3) \ P_{sh} + P_{ti} + P_{ri} \leq q_i B_i \quad \forall i \in \mathcal{N}, \\
& 4) \ \sum_{i \in \mathcal{N}} a_{il} q_i = 0 \quad \forall l \in \mathcal{L}, \\
& 5) \ \sum_{h \in \mathcal{V}} x_{hl} \leq W \log_2 \sqrt{1 + \frac{P_{rl}}{N_0 W}} \quad \forall l \in \mathcal{L}, \\
& 6) \ \sum_{l \in \mathcal{L}} a^+_{il} P_{t_l} \leq P_{t_{max}} \quad \forall i \in \mathcal{N}, \\
& 7) \ \sum_{l \in \mathcal{L}} a^-_{il} P_{r_l} \leq P_{r_{max}} \quad \forall i \in \mathcal{N}, \\
& 8) \ dist(i, \mathcal{S}) = \min_{j \in Nbrs_i} [dist(i, j) + dist(j, \mathcal{S}) \\
& \qquad \mid \ dist(i, \mathcal{S}) \geq dist(j, \mathcal{S})] \quad \forall i \in \mathcal{N}, \\
& 9) \ \mathcal{R}_l \geq RequiredReliability_l, \quad \forall l \in \mathcal{L}, \\
& 10) \ \ Rh \geq \sum_{l \in \mathcal{L}} a^+_{il} C_l \ \ \forall h \in \mathcal{V}, \forall i \in \mathcal{N} \\
& 11) \ a^+_{il} = \{0, 1\} \quad \forall i \in \mathcal{N} \ \forall l \in \mathcal{L}, \\
& 12) \ a^-_{il} = \{0, 1\} \quad \forall i \in \mathcal{N} \ \forall l \in \mathcal{L}, \\
& 13) \ x_{hl} \geq 0, R_h \geq 0, P_{sh} > 0, q_i > 0.
\end{aligned}
\tag{6.9}
$$

Due to the rich structure of this problem (6.9), and similarly to the problem presented in (6.3), a decomposition approach can also be applied to the latter. Accordingly, the original optimization problem (6.9) can be decomposed into two subproblems, as follows:

$$
\begin{aligned}
&\textbf{P3:}\min_{(q,R,x,P_s)} \sum_{i\in N} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_{h} R_h^2 + \delta_p \sum_{h} P_{sh}^{8/3}\\
&\text{subject to } (1),(2),(3),(4),(5),(6),(7),(13).\\
&\textbf{P4:}\min_{(a_{il}^+,a_{il}^-)} U^*(a_{il}^+,a_{il}^-)\\
&\text{subject to } (8),(9),(10),(11),(12).
\end{aligned}
\tag{6.10}
$$

Let us recall that the $U^*(a_{il}^+, a_{il}^-)$ can be viewed as the optimal value for the **P3** problem, and used to resolve the latter.

6.8.1/ P3 RESOLUTION

In addition to the iterative calculation of the Lagrange multipliers described in section (6.5.2.2), and using the subgradient method [18], the Lagrange multipliers, *i.e.*, Γ, Z and ζ, added to the Fifth, Sixth and Seventh constraints, respectively, can be calculated as follows:

$$
\begin{aligned}
&\Gamma_l^{k+1} =\\
&\quad \max\left\{0, \Gamma_l^k - \theta^k\left(W\log_2\sqrt{1+\frac{P_{rl}^k}{N_0W}} - \textstyle\sum_{h\in\mathcal{V}} x_{hl}^k\right)\right\},\\
&Z_i^{k+1} = \max\left\{0, Z_i^k - \theta^k\left(P_{t_{max}} - \textstyle\sum_{l\in\mathcal{L}} a_{il}^+ P_{tl}^k\right)\right\},\\
&\zeta_i^{k+1} = \max\left\{0, \zeta_i^k - \theta^k\left(P_{r_{max}} - \textstyle\sum_{l\in\mathcal{L}} a_{il}^- P_{rl}^k\right)\right\}.
\end{aligned}
\tag{6.11}
$$

Finally the primal variables (q_i^k, P_{sh}^k and R_h) can be calculated as described in section 6.5.2.2 to obtain a fully distributed solution. However, the calculation of the x_{hl}^k primal variable is more complicated, since the latter appears inside the logarithm when applying the Shannon's formula. From chapter 4 section 4.3 the latter can be calculated as follows:

$$
\begin{aligned}
&x_{hl}^k =\\
&\max\Big\{0, \tfrac{-1}{2\delta_x}\big(\textstyle\sum_{i\in N} u_{hi}^k a_{il} + c_l^s \sum_{i\in N} \lambda_i^k a_{il}^+ + c^r \sum_{i\in N} \lambda_i^k a_{il}^-\\
&+\Gamma_l^k + c_l^s \textstyle\sum_{i\in N} Z_i^k a_{il}^+ + c^r \sum_{i\in N} \zeta_i^k a_{il}^- - \frac{c^r \Gamma_l^k}{2N_0 \ln 2}\big)\Big\}.
\end{aligned}
\tag{6.12}
$$

The distributed optimization Algorithm 2 summarizes the resolution of the **P3** optimization problem

6.8.2/ P4 RESOLUTION

Let us now discuss the updating of the coupling variable (a_{il}^+, a_{il}^-), based on the localized hop-by-hop routing protocol.

Each node i executes first the distributed optimization algorithm P4 described in Algorithm 3, that has as an input the required reliability ($RequiredReliability_l$, $l \in \mathcal{L}$) defined by the application layer, and starts by identifying all the neighboring nodes (**step1**, lines 3-9). In this step, called the neighboring discovery phase, a node j is considered as a neighbor of i if the Euclidean distance between the two nodes is inferior or equal to the defined communication range ($ComRange$). Once the neighboring nodes are discovered, the estimation of the links reliability starts by executing a simple ping processus (**step2**, lines 10-13), using the formulation (6.7).

Achieving this point, each node i has the necessary information in order to select the *first* best downstream node. To do so, the node i identifies a candidate downstream node j ($j \in Nbrs_i$) that produces the geographic progress toward the sink node ($\mathcal{S}$) (*i.e.*, constraint (8)), ensures a shortest path (*i.e.*, constraint (9)) and respects at the same time the required reliability by the application layer (*i.e.*, constraint (10)). Once these conditions are met, it stores it in the routing table, updates the a^+_{il} and a^-_{il} matrices and informs all its neighboring nodes (**step3**, lines 14-21).

Let us know explain the main part of our algorithm that allows to cross the two axes, namely, the data processing axis and the routing axis. After the update of the a^+_{il} and a^-_{il} matrices, each node i can indeed starts the execution of the distributed optimization algorithm **P3** described in Algorithm 2, in order to update the processing axis parameters (*i.e.*, P_{sh}, R_h, x_{hl}, q_i) until a certain number of iterations (ItThreeshold). Once this threshold is reached, the Distributed optimization algorithm P4 (Algorithm 3-**step4** line 23) is called with an updated R_h and C_l.

Then, each node i verifies if $Rh \geq \sum_{l\in\mathcal{L}} a^+_{il}C_l$, $\forall i \in \mathcal{N}$. If it returns *True*, the node i executes **step 3** in order to select the *second* best downstream node. Then recalls the distributed optimization algorithm P3 with the updated a^+_{il}, a^-_{il} and ItThreeshold as an input.

Note that these steps are repeated until $Rh \leq \sum_{l\in\mathcal{L}} a^+_{il}C_l$, $\forall i \in \mathcal{N}$.

Algorithm 2 Distributed optimization algorithm P3 (DOAP3)

```
Input: a+_il, a-_il, i ∈ N, l ∈ L, ItThreeshold
Initialize: Set k = 1 and P_sh^(k), R_h^(k), x_hl^(k), q_i^(k), u_hi^(k), v_h^(k), λ_h^(k), w_l^(k), Γ_l^k, Z_i^k, ζ_i^k to any initial point.
step 1:
each node i ∈ N and h ∈ V
    calculates u_hj(j∈Nbrs_h)^(k+1), v_h^(k+1), λ_h^(k+1), w_l^(k+1), Γ_l^(k+1), Z_i^(k+1), ζ_i^(k+1), q_i^(k+1), P_sh^(k+1), R_h^(k+1);
    transmits λ_h^(k+1), q_i^(k+1), Z_i^(k+1) and ζ_i^(k+1) to one-hop neighboring;
end step 1
At the reception of λ_h^(k+1), Z_i^(k+1) and ζ_i^(k+1)
step 2:
each node h ∈ V
    calculates x_hl^(k+1);
    transmits x_hl^(k+1) to one-hop neighboring;
end step 2
repeat
    step 1
    step 2
until {NumIteration==ItThreeshold || the range of q_i == T}
if (NumIteration==ItThreeshold) then
    Call DOAP4-step 4, with the updated R_h, h ∈ V, and C_l, l ∈ L as an input
end if
```

6.8.2.1/ Path reliability

The end-to-end path reliability is difficult to address, and can be defined by the application layer. Since the latter is multiplicative over each path, the variation of only one link over this path can highly reduce the end-to-end reliability performance. Taken as an example, the end-to-end reliability requirement of 85% and only 4 hops to reach the destination from the source node. Note that, even if the reliability of each of the 4 links is of 85% then the path is not feasible to satisfy the end-to-end reliability requirement. To achieve a such reliability, the mean of reliability on the 4 links has to be 97%, which is very restrictive in wireless multimedia sensor networks. Thus, this point should be considered during the link reliability definition.

Algorithm 3 Distributed optimization algorithm P4 (DOAP4)

Input: $RequiredReliability_l$, R_h, C_l, $\forall h \in \mathcal{V}$, $\forall l \in \mathcal{L}$
Initialize: Set a^+_{il}, a^-_{il} ($\forall i \in \mathcal{N}$, $\forall l \in \mathcal{L}$) to zero, $ComRange = 30$
step 1:
each node $i \in \mathcal{N}$ **and** $h \in \mathcal{V}$
    Broadcast *HelloMsg*(ID_i,x_i,y_i);
if ($dist(i, j) \leq ComRange$, $\forall j \in Nbrs_i$) **then**
    HelloReply(ID_j,x_j,y_j);
end if
end step 1
step 2:
ping(j), $\forall j \in Nbrs_i$;
return $\mathcal{R}_l$;
end step 2
step 3:
min=inf
if(($dist(i, \mathcal{S}) > dist(j, \mathcal{S})$) && ($dist(i, j) + dist(j, \mathcal{S}) < min$)) && ($\mathcal{R}_l \geq RequiredReleability_l$)) **then**
    min $\leftarrow (dist(i, j) + dist(j, \mathcal{S}))$;
    Update(a^+_{il}, a^-_{il});
    InformNbrs(i);
end if
end step 3
step 4:
Call DOAP3 with the updated (a^+_{il}, a^-_{il}), $\forall l \in \mathcal{L}$, as an input;
if (NumIteration==ItThreeshold && (*Verify*((R_h,C_l)==*True*) **then**
    execute **step3**;
    ItThreeshold= ItThreeshold*2;
else
    execute **step4**;
end if
end step 4

6.8.2.2/ PING PROCESS

In order to estimate the reliability of each constructed link, each video sensor node i sends a certain number of packets to each neighboring node j attached with a sequence number. At the reception of these packets, each node j ($\forall j \in Nbrs_i$) computes the $\mathcal{R}_l$, $\forall l \in \mathcal{L}$, as described in (6.7). Then, it sends back the estimated reliability of the link to the source node i.

6.8.2.3/ PATH CONFIRMATION

In contrast to the solution proposed in section 6.5.2.1, where each node receives the list of the adequate downstream nodes from the sink through the inverse path, in this solution, each node relies on local information to make the decision. In fact, based on the links reliability and on the updating of the outgoing and incoming links(through the updating of the R_h and C_l), each node selects and maintains the adequate number of paths in order to achieve the optimal routes between the latter and the sink.

6.8.2.4/ DISJOINT PATH

Based on the data rate R_h at the source node h and the links capacity C_l on all the outgoing links l from node h, each node decides locally about the sufficient number of paths that should be considered. If more than one path is selected, then the source node h chooses the second node j, $j \in Nbrs_h$, that is totally different from the first best neighbor node, and that ensures not only a geographic progress toward the sink, but also respects the required reliability by the application layer.

6.9/ SIMULATION RESULTS

In this stage of simulation, we use the same parameters initialization values of the video sensors as presented in chapter 3, section 3.7, table 3.1. Then, we set the transmission and reception maximal powers to $P_{t_{max}} = 2.63$ W and $P_{r_{max}} = 1.5$ W, respectively. In addition to these parameters, and in order to evaluate the performance of our solution, we have chosen to evaluate it through two different topologies. The first topology is the one presented in figure 6.1, in which the sink was placed at the corner of the network, while in the second topology, the sink was placed in the middle of the network as shown in figure 6.7. The aim behind moving the sink is to test the well functioning of the proposed solution.

6.9.1/ CONVERGENCE OF THE PROPOSED SOLUTION

The convergence of the auxiliary variable q_i to a common q, can be observed in the Figure 6.8.(a) and Figure 6.8.(b) for the first (T1) and second (T2) topologies, respectively. Similarly to the convergence results in section 6.6.1, we consider the system as completely stable when the maximum variation between the q_i is $T = 10^{-2}$.

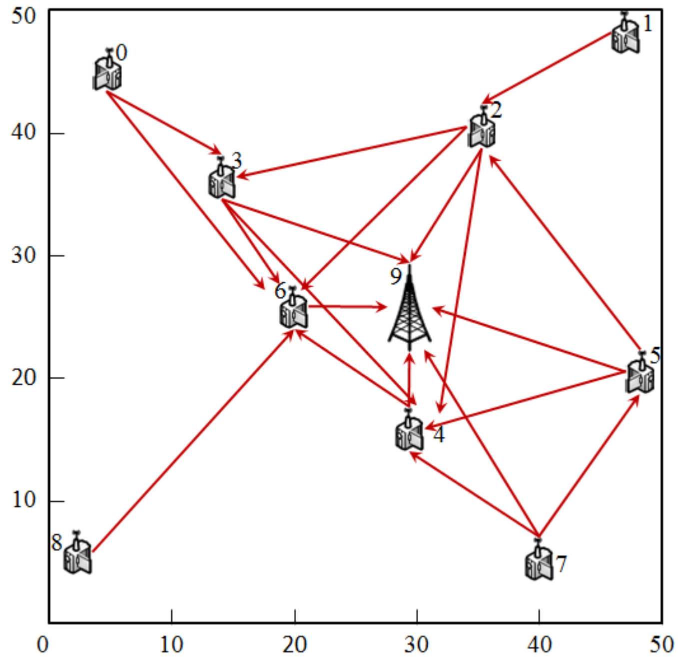
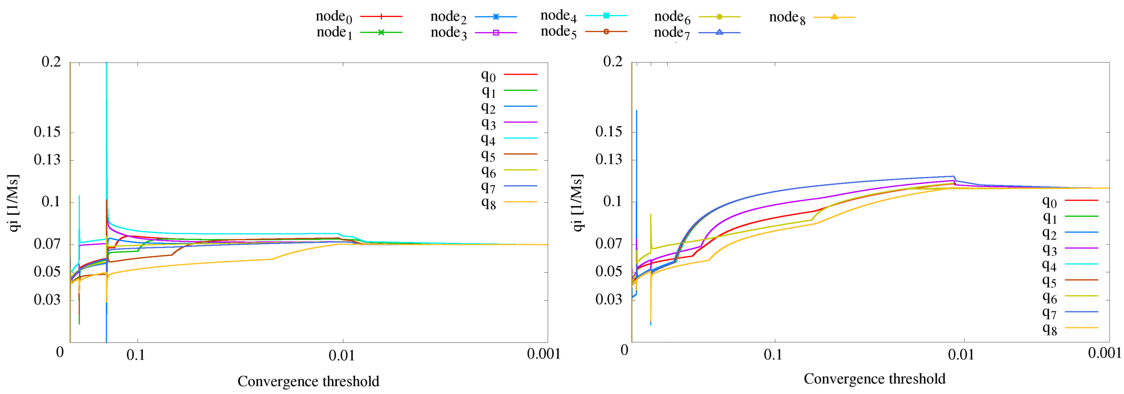


Fig. 6.7: Network topologies: T1 and T2, respectively.

The peaks in figures 6.8.(a) and 6.8.(b) can also be observed. These peaks mean that, the correspondent node has chosen to add an additional path after the data rate R_h and links capacity C_l verification, in order to choose the adequate number of paths to be used. Note that the duration of each peak is very small and even negligible and is about $2.17s$ using the MiXiM-2.3 framework that was integrated into the omnet++-4.6 simulator.



(a) First topology

(b) Second topology

Fig. 6.8: Auxiliary variables for the first topology

Before going further, let us discuss the choice of the sufficient number of paths and how it works. Since both experimentations on the two different topologies lead to the same conclusion, the focus will only be on results of the first topology (T1). Table 6.2 shows two cases: the first one, when the node needs to have 3 paths, while in the second case, the node needs to have only 2 paths in order to achieve the performance demands of the

Table 6.2: Link's capacities Vs link's rates

Nodes	*paths*	R_h Mbps (1st.pr)	C_l Mbps(2nd.pr)	*sufficiency*
0	1 path	R_0= 0.191541	C_0= 0.0736882	*not suff*
	2 paths	R_0= 0.180875	C_0= 0.0855795	*not suff*
			C_1= 0.0800058	
	3paths	R_0= 0.17962	C_0= 0.0644174	*suff*
			C_1= 0.0563247	
			C_2= 0.0645586	
5	1path	R_5= 0.193454	C_{15}= 0.0766058	*not suff*
	2 paths	R_5= 0.179622	C_{15}= 0.0980251	*suff*
			C_{16}= 0.0873981	

target application.

From the table above, we can observe that the data rate R_0 is much bigger than the link capacity C_0 that connects node 0 to its first best neighbor node. To cope with this problem, node 0 chooses its second best downstream node (connected by link $l = 1$, in this experimentation). However, both paths seem to be insufficient for the data transmission. Thus, node 0 has to select another downstream node which is considered as the third best neighbor node, instead of node 5 where the selection of only two paths seems to be the adequate number of paths to be used (*i.e.*, $R_5 < C_{15} + C_{16}$).

The main advantage of such a downstream node(s) selection is the progressive path discovery, making it possible to choose not only the best path(s) toward the sink node, but also, to select the sufficient number in order to preserve the energy of each node and thus extend the network lifetime.

6.9.2/ Optimization cost

In this subsection we analyze the cost of the optimization steps in terms of energy and duration at each node for the first and second topologies.

6.9.2.1/ Energy cost

Figure 6.9.(a) and Figure 6.9.(b) depict the percentage of battery consumption of each video sensor node, for the first and second topology, respectively. The latter concerns the total energy requirement for the optimization steps of both **P3** and **P4**. It can be observed that the energy consumed by the highest consumer node in term of battery, in order to ensure the convergence, did not exceed 0.025% and 0.08% for the first and second topology, respectively. Thus, it can be concluded that the optimization step including both **P3** and **P4** consumes a negligible amount of energy.

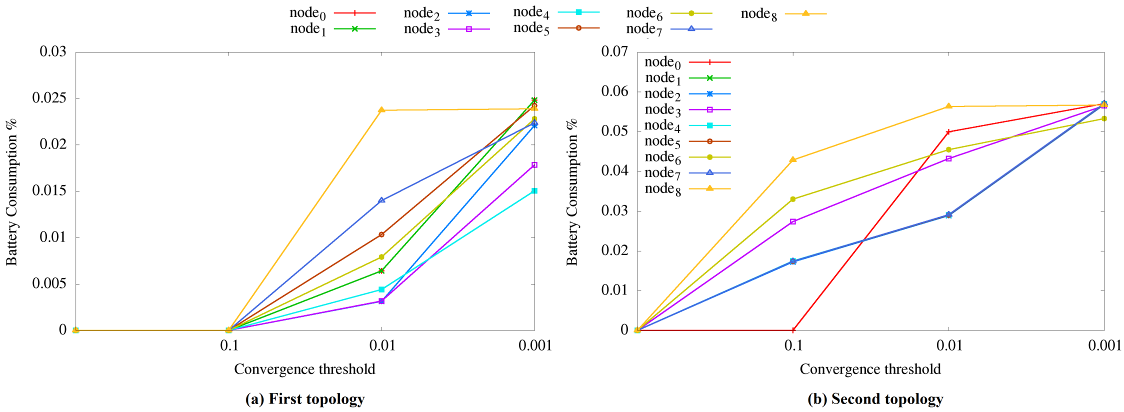


Fig. 6.9: battery consumption of optimization steps for the first topology

6.9.2.2/ Optimization steps duration

Let us now evaluate the duration (in minutes) of the optimization step needed for the system convergence. Figure 6.10.(a) (first topology) and Figure 6.10.(b) (second topology) present the optimization step duration including both **P3** and **P4**, for each threshold $T \geq 10^{-3}$. It can be observed that the optimization duration differs from one topology to another, here the optimization duration of the second topology exceeds the optimization duration of the first one. This difference can be explained by the adequate number of paths selected by each video node. Note that, the smaller the number of the selected paths is, the bigger the number of iterations required for the system to converge is, and thus, the longer the optimization duration last.

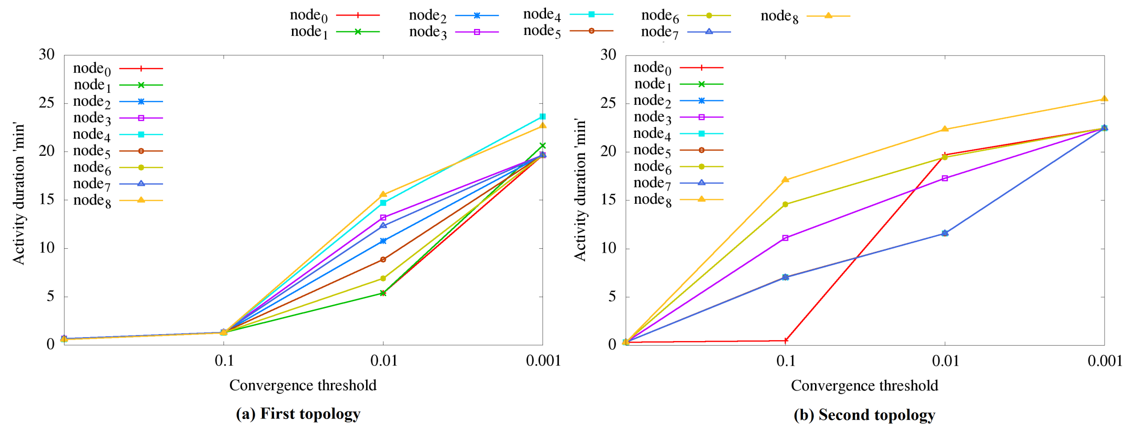


Fig. 6.10: Optimization duration for the first topology

6.9.3/ Node lifetime improvement

Let us recall that, the node lifetime is calculated as follows: $T_i = B_i/P_i$.

At this stage of the evaluation, we focus on the remaining lifetime of each video node after each convergence threshold. Taking into account that the network lifetime is defined by the node that has the lowest lifetime, Figure 6.11.(a), and Figure 6.11.(b) show the improvement of nodes lifetime for the first and second topology, respectively. It can be observed that the network lifetime has been increased by increasing the lowest node lifetime (namely. node 3 for the first topology and node 0 for the second topology) by at least 7.47 times for the first topology and by 7.67 times for the second one.

This improvement demonstrates the efficiency of the integration of the routing into the analytical model, while respecting the reliability of each path and selecting the sufficient number of paths in order to prolong the network lifetime and respect the desired video quality at the destination level.

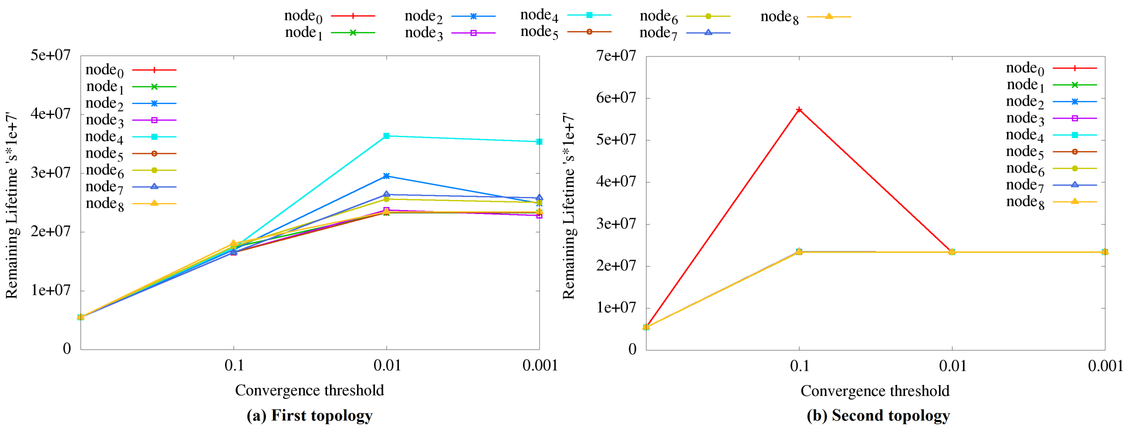


Fig. 6.11: Remaining lifetime after each convergence threshold for the first topology

6.10/ Conclusion

In this chapter and based on our previous work on power/rate tradeoff for network lifetime maximization, a new analytical model for video encoding and multimedia content delivery has been proposed. The optimization problem was solved over a two level optimization, through which each video sensor node chooses the best downstream node(s) based on: the link reliability, the data rate of the video node and the capacity of each link. At the same time, the trade-off between the encoding power at the source level and the desired video quality at the destination level is ensured.

Simulation results prove the efficiency of the proposed solution, given its minimal requirements in terms of computational power and energy consumption, while ensuring the desired video quality at the destination level.

Let us note that, in this chapter once the reliability is determined, the latter remains unchangeable. Additionally, the energy of the intermediate nodes was not considered. Thus, the next chapter tackles the problem of the dynamic link's reliability, as well as the intermediate node's energy problem.

7

Joint Data-Processing/Data-Transmission for Network Lifetime Maximization in Dynamic Wireless Video Sensor Networks

In chapter 6, an efficient distributed data-processing/data-transmission combination have been proposed. The latter, consider the reliability and the capacity of each link in order to select the adequate number of paths required to transmit the generated data (after the compression process) and thus to preserve the desired video quality at the destination level. However, once the reliability determined, the latter was maintained and remained unchangeable. Furthermore, the remaining energy of the intermediate nodes was not considered. Thus, one major problem remains and can be resumed as follows: *How can this approach resist against path loss over unreliable and dynamic networks?*

From that, and to complete the study of chapter 6, we propose, in this chapter, a fully distributed solution that takes into account the dynamic change of link's reliability based on probabilistic perturbation distribution. Additionally, this solution dynamically changes the capacity of links depending on the remaining energy of the concerned nodes. Simulation results show that the proposed algorithm is highly responsive to the changes of topology.

7.1/ Data routing concerns

As the data processing, the delivery of multimedia content has also a major impact on network lifetime as shown in chapter 5. Thus, finding the optimal number of path(s) while considering: **(a)** the limited resources of video sensor nodes, **(b)** the dynamic changes of both reliability and capacity of each link is a complex task. In this section, we present the different formulas needed to overcome the aforementioned requests.

7.1.1/ Dynamic link's capacity

The environments in which the multimedia nodes operate are dynamic. Two of the parameters that might change dynamically are the generated traffic and the power availability. Thus, depending on the received data and the percentage of the remaining power R_{pi} of node i, the capacity C_l of each link l can be formulated as follows:

$$C_l^{k+1} = R_{pi}^{k+1} W \log_2 \sqrt{1 + \frac{P_{rl}^k}{N_0 W}} \quad \forall l \in \mathcal{L}, \tag{7.1}$$

The main objective to do so, is to prolong the node lifetime and thus prologuing the whole network lifetime.

Thus the constraint (10) in the analytical model proposed in chapter 6, section 6.8 should be replaced by $R_h \geq \sum_{l \in \mathcal{L}} R_{pi} a_{il}^{+} c_l$, $\forall h \in \mathcal{V}, i \in \mathcal{N}$.

7.1.2/ Multipath routing

The multipath routing approach has the potential to enable low power consumption, and high data-rate transmission. This approach can be used either to split the data over the existing paths, or to duplicate data across these latter. Our scheme falls into the first category.

Our algorithm of distributed nature allows a selection of the exact number of paths needed for data transportation. To do so:

- Firstly, each node discovers its one hop neighbors by sending a simple *HELLO* message, to determine the number of existing paths.
- Once the paths are determined, each node chooses its best downstream node based on: **a)** the Euclidian distance to the sink and **b)** the link reliability that connects these nodes.
- Then, and different from chapter 6, each node h compares the link capacity C_l (that takes into account the remaining energy of the intermediate node as shown in equation (7.1)) of its outgoing link with the multimedia traffic (R_h) generated by this node (h).
- if C_l is greater then R_h the node considers that this is the required number of paths. Otherwise, it selects its next best downstream node.

Note that, if the number of the required paths is greater or equal to two paths, the exact formula is as follows: $R_h \leq \sum_{l \in \mathcal{L}} R_{pi} a_{il}^{+} C_l$, $\forall i \in \mathcal{N}\ \forall h \in \mathcal{V}$

Thus, if the capacity of a given link decreases or a sudden change of link reliability occurs, our algorithm can adapt and dynamically finds out a series of multiple paths to complete the data delivery.

7.1.3/ Dynamic reliability

Another parameter that can dynamically change is the reliability of a chosen path. The latter can be defined as shown in chapter 6, equation (6.7) and (6.7)

7.2/ Optimization Problem formulation and resolution

As previously mentioned, our goal is to handle the dynamic change of both: link's reliability and link's capacity. Let us recall that, link's capacity changes depending on the remaining energy of the intermediate nodes, while the link's reliability can suddenly change due to the hard characteristics of the wireless medium (*i.e.*, interferences, link failure, congestion, etc.).

In order to achieve such requests, and by replacing the constraint (10) in the analytical model proposed in chapter 6, section 6.8, the optimization problem formulation 6.9, which combines the routing and data processing constraints, can be reformulated as follows:

$$
\begin{aligned}
\underset{(q,R,x,P_s)}{\text{minimize}} \quad & \sum\nolimits_{i\in\mathcal{N}} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_h R_h^2 + \delta_p \sum_h P_{sh}^{8/3} \\
\text{subject to:} \quad & 1)\ \sum_{l\in\mathcal{L}} a_{il}x_{hl} = \eta_{hi} \quad \forall h\in\mathcal{V}\ \forall i\in\mathcal{N}, \\
& 2)\ \sigma^2 e^{-\gamma R_h P_{sh}^{2/3}} \le D_h \quad \forall h\in\mathcal{V}, \\
& 3)\ P_{sh} + P_{ti} + P_{ri} \le q_i B_i \quad \forall i\in\mathcal{N}, \\
& 4)\ \sum_{i\in\mathcal{N}} a_{il}q_i = 0 \quad \forall l\in\mathcal{L}, \\
& 5)\ \sum_{h\in\mathcal{V}} x_{hl} \le W\log_2\sqrt{1+\frac{P_{rl}}{N_0 W}} \quad \forall l\in\mathcal{L}, \\
& 6)\ \sum_{l\in\mathcal{L}} a_{il}^{+}P_{t_l} \le P_{t_{max}} \quad \forall i\in\mathcal{N}, \\
& 7)\ \sum_{l\in\mathcal{L}} a_{il}^{-}P_{r_l} \le P_{r_{max}} \quad \forall i\in\mathcal{N}, \\
& 8)\ dist(i,\mathcal{S}) = \min_{j\in Nbrs_i} [dist(i,j) + dist(j,\mathcal{S}) \\
& \qquad \mid dist(i,\mathcal{S}) \ge dist(j,\mathcal{S})] \quad \forall i\in\mathcal{N}, \\
& \mathbf{9)}\ \mathcal{R}_l \ge RequiredReliability_l, \quad \forall l\in\mathcal{L}, \\
& \mathbf{10)}\ R_h \ge \sum_{l\in\mathcal{L}} R_{pi}a_{il}^{+}C_l \quad \forall h\in\mathcal{V}, \forall i\in\mathcal{N} \\
& 11)\ a_{il}^{+} = \{0,1\} \quad \forall i\in\mathcal{N}\ \forall l\in\mathcal{L}, \\
& 12)\ a_{il}^{-} = \{0,1\} \quad \forall i\in\mathcal{N}\ \forall l\in\mathcal{L}, \\
& 13)\ x_{hl} \ge 0, R_h \ge 0, P_{sh} > 0, q_i > 0.
\end{aligned}
\tag{7.2}
$$

Unlike our previous chapter 6, where the reliability were stable and the link's capacity did not consider the energy of the intermediate nodes. In this mathematical model, the reliability of each link is dynamic (constraint **(9)**) and the capacity of each incoming link l to node i changes depending on the remaining energy (R_{pi}) of the latter (i) as it was presented in constraint **(10)**. These two constraints present the difference between the previous mathematical model (6.9) and the one presented above (7.2)

Due to the rich structure of this problem and similarly to chapter 6, a decomposition approach can be applied in order to split the latter into a set of small subproblems. Thus, these latter can be solved in a distributed manner and converge to the global optimum [93]. Firstly, a primal decomposition with respect to the coupling variables (a_{il}^{+}, a_{il}^{-}) is required. Then, the dual problem can be formulated with respect to the coupling constraints (1-7) and (13). Finally, the original optimization problem (7.2) can be decomposed into two subproblems as follows:

$$\begin{aligned}
&\textbf{P1:}\min_{(q,R,x,P_s)} \sum_{i\in N} q_i^2 + \delta_x \sum_{h,l} x_{hl}^2 + \delta_r \sum_h R_h^2 + \delta_p \sum_h P_{sh}^{8/3} \\
&\text{subject to } (1),(2),(3),(4),(5),(6),(7),(13). \\
&\textbf{P2:}\min_{(a_{il}^{+},a_{il}^{-})} U^*(a_{il}^{+}, a_{il}^{-}) \\
&\text{subject to } (8),(9),(10),(11),(12).
\end{aligned} \tag{7.3}$$

Note that, the **P1** resolution can be achieved as in chapter 6, section 6.8.1. In contrast, the **P2** resolution, that consists of determining the outgoing (a_{il}^{+}) and incoming (a_{il}^{-}) routing matrices, can be achieved as follows:

- Firstly, each node identifies all the neighboring nodes. In this step, a node j is considered as a neighbor of i if the Euclidean distance between the two nodes is less or equal to the defined communication range ($ComRange$).
- Once the neighboring nodes are discovered, the estimation of the links reliability starts by executing a simple ping processus, using the formulation (6.7).
- Then, each node chooses its first best downstream node based on two conditions: **(a)** the chosen node respects the lower theoretical bound of reliability on the link l (formula (6.8)), **(b)** the chosen node produces the geographic progress toward the sink node and ensures the shortest path compared to the other potential downstream nodes.
- Achieving this point, the first (but not the optimal) update of the a_{il}^{+} and a_{il}^{-} routing matrices can be done and send to the P1 problem. The latter will use these two matrices in order to update the primal and dual parameters and send back: R_h, R_{pi} and C_l to P2.
- Once P2 receives these parameters, each node i proceeds by comparing if $R_h \geq \sum_{l\in\mathcal{L}} R_{pi} a_{il}^{+} C_l$, $\forall i \in \mathcal{N}$. If it returns *True*, the node i selects the *next* best downstream node. Then recalls the distributed optimization algorithm P2 with the updated a_{il}^{+}, a_{il}^{-}.

Thus, the P1 and P2 problems keep interchanging the required parameters, as shown in figure 7.1, until the stabilization of the routing matrices (*i.e.*, when $R_h \leq \sum_{l\in\mathcal{L}} R_{pi} a_{il}^{+} C_l$, $\forall i \in \mathcal{N}$) and the convergence of all the q_i of the system to a common value (q).

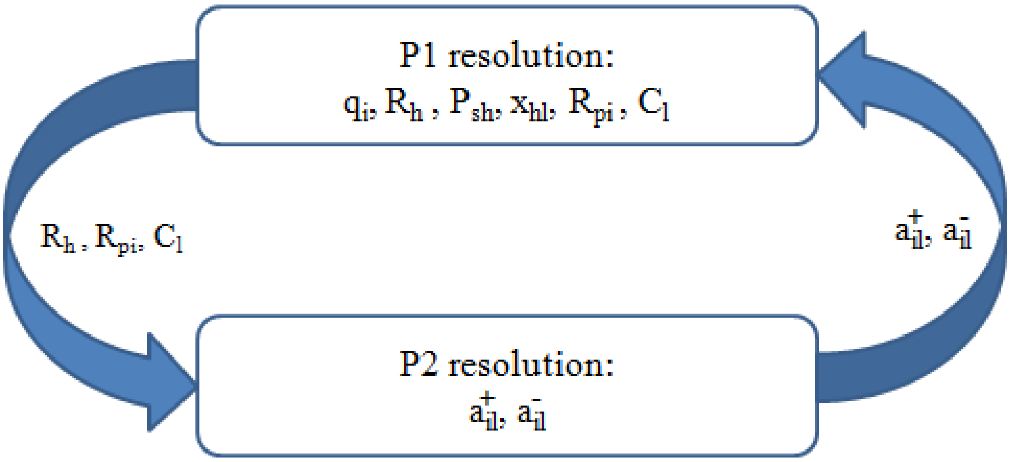


Fig. 7.1: P1 and P2 interconnection

7.3/ Data sending phase

Note that, in the proposed solution the sending of data starts once the encoding power (P_{sh}) and the data rate (R_h) are stable (*i.e.*, during the optimization steps) which will be explained in the simulation results section. Thus, once the convergence of the system is achieved, the optimization phase ends and only the sending of data will continue. During the data sending phase (after the optimization steps) each node $h \in \mathcal{V}$ proceeds as follows:

- It sends its own data to its one hop neighboring nodes, while multiplying the capacity of its incoming links by the percentage of its own remaining energy.
- After a certain number of data sent, the delivery of the data rate R_h of the given node h can not be further ensured (*i.e.*, $R_h > \sum_{l \in \mathcal{L}} a^+_{il} C_l$, $\forall i \in \mathcal{N}$). This situation means that, the node h requires an additional path in order to save the final video quality at the sink level.
- Thus, the node h firstly starts by checking the existence of an additional path with respect to the link reliability.
- If an additional path exists, the node h returns to the optimization steps phase and informs its one hop neighboring nodes (which will in turn inform their neighboring nodes). Gradually, all the nodes in the network return to the optimization steps phase. Once the convergence of the system is ensured again, the data sending phase is evoked.
- Otherwise, the node h will continue to send data to the detriment of video quality at the destination level (*i.e.*, the distortion will increase).

Until this point, each node chooses the required number of paths in order to transmit the multimedia content to the sink node. Such a choice is based on not only the reliability of each link, but also depending on the capacity of each link which is heavily affected by the energy of each node (since the latter decreases with respect to the decreasing of the remaining energy).

Let us now discuss how to cope with the sudden changes of link's reliability, due to the link or node failures. Thus, the main objective of this part can be resumed as follows: *How this approach can resist against path loss over unreliable networks?*

To do so, multipath routing seems to be the only suitable routing to tackle with such a problem. The main objective behind this latter is to combine the resources of the existing multiple paths in order to transmit data from the source to the destination.

Before going further, let us discuss the implications of such a solution. In fact, deleting or adding a new link into the system (*i.e.*, updating the routing tables a_{il}^{+} and a_{il}^{-}) requires the recomputing of all the needed parameters in order to ensure the correct functioning of the system. Thus, it requires additional iterations to ensure the convergence of the latter and thus additional battery consumption.

In order to evaluate the performance of our proposed resilient approach against the link failures, we have conducted several series of simulations under different types of perturbations that can be explained as follows:

- **Successive Perturbation Distribution (SPD):** the SPD can be defined by the sudden change of the reliability of some links in the network in a contiguous manner. Indeed, in some cases, a node may be the only point of connection between two communicating nodes (in Figure 7.2.a, the nodes 3 and 4 are considered as a connection nodes). Consequently, the failure of the incoming links of such nodes causes the partition of the network into multiple disjoint parts, referred to by blue clouds in Figure 7.2.b. In this case, and in order to detect the infected links, the reliability of these latter is set to zero.

- **Uniform Perturbation Distribution (UPD):** In UPD, the perturbations are uniformly distributed across the whole network. A simple example of such a case, is the existence of an obstacle (*i.e.*, wall, snow, leafs, or other objects placed near the video node) between two video nodes. In the case of uniform perturbation distribution, the obstacles will not break the connectivity between the nodes, but reduce the strength of the latter. Thus, it can be expressed by reducing the reliability of the concerned links.

- **Gaussian Perturbation Distribution (GPD):** In GPD, the perturbation is produced following a Gaussian distribution. Since the values of link's reliability are contained in the interval [0,1], the chosen mean of such a distribution is 0.75 due to the hard reliability condition (*i.e.*,the reliability is multiplicative on the same path). In this type of perturbation, the link can see its reliability value increasing, decreasing or even keeping the same reliability value.

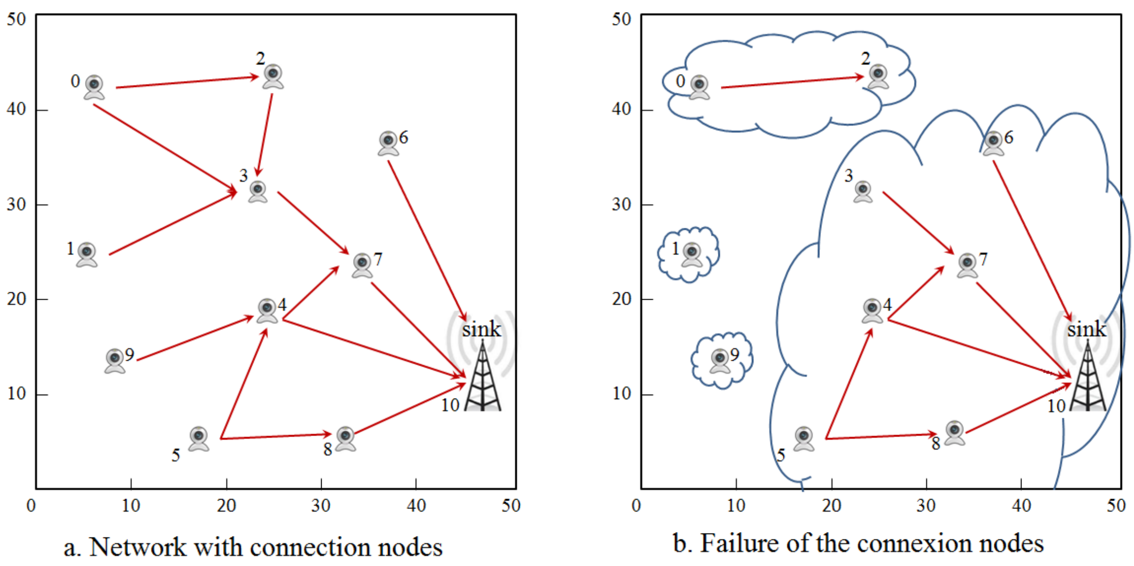


Fig. 7.2: Successive perturbations example

7.4/ Simulation results

In this stage of simulation, we use the same parameters initialization values of the video sensors as presented in chapter 3, section 3.7, table 3.1.

The network configuration used in this chapter is the same as presented in chapter 3, figure 3.2.

7.4.1/ Convergence of the system

Before going further, figure 7.3 shows the convergence of variables q_i to a common value q of the successive, uniform and gaussian perturbations. The convergence of the system means that the latter is completely stable and functional.

Since the main objective of this paper is to find an optimal trade-off between the encoding power, the data rate and the routing of the data, table 7.1 shows the stabilization of both the encoding power (P_{s6}) and the data rate (R_6) even before the convergence of the system to a threshold of $T = 10^{-2}$. Thus, in the rest of this chapter, we consider the system as functional when the convergence threshold T is equal to 10^{-2}, since more is the requirement of the precision (*i.e.*, $T < 10^{-2}$), more is the energy consumption and the duration of the optimization steps. Additionally, we have chosen to send the real data after the stabilization of the encoding power and the data rate.

Note that, we have chosen the node 6 in table 7.1 since the latter is the latest node whose q_6 converges to the common value q.

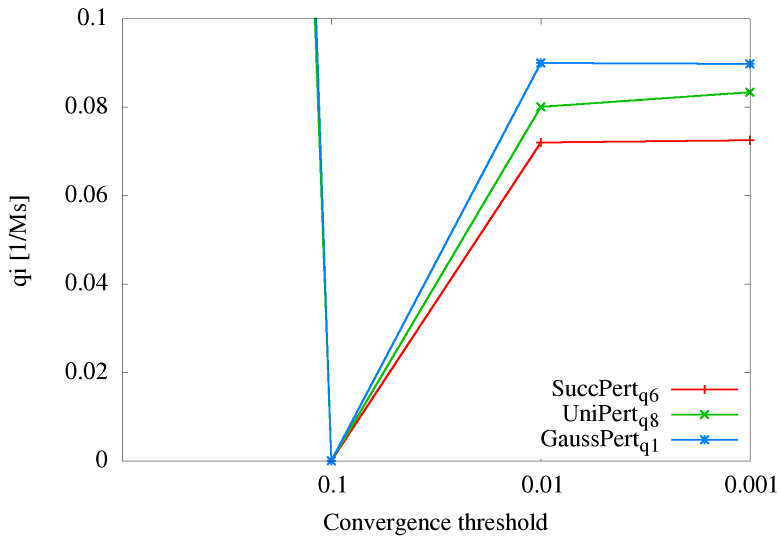


Fig. 7.3: Convergence to a common value q

Variables/Threshold	0.1	0.01	0.001
q_6 (min)	0.0001	12.98	26.68
P_{s6} (min)	0.000156	1.56	8.58
R_6 (min)	0.00011	2.24	11.14

Table 7.1: dual variables convergence duration

7.4.2/ ENERGY COST FOR THE OPTIMIZATION STEPS

Figure 7.4 shows the energy requirement during the optimization steps until the convergence of the system for the successive, uniform and gaussian perturbations. In this figure we have chosen the nodes with the highest energy consumption (*i.e.*, node5, node1 and node1 for successive, uniform and gaussian perturbations, respectively, as well as node8 for the basic solution without perturbations). Firstly, it can be observed that the basic solution requires the lowest energy consumption which was expected, since the latter runs without perturbations. Secondly, it can be seen that the solution with successive perturbation requires the highest energy consumption compared to the uniform and gaussian ones. This observation can be explained by the fact that the latter has lost a part of the network, as it can be shown in figure 7.5-a. Thus, in order to reach the sink node, an other path should be found as shown in figure 7.5-b which requires more energy. Additionally, the found path ensures minimal communication between the two ends of the network, which means that it requires more iterations to ensure the convergence of the system and hence more energy consumption. Even though, it should be mentioned that the battery consumption, even with perturbations, did not exceed 0.16% of the total battery, and this shows the efficiency of our solution.

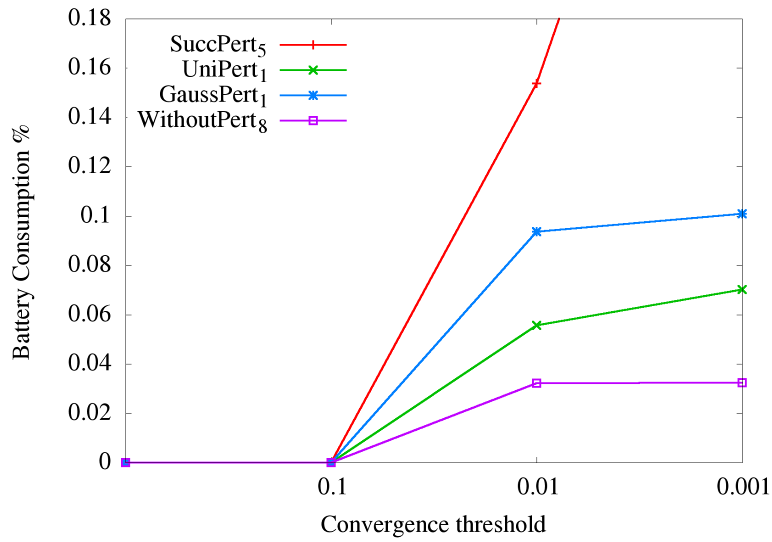


Fig. 7.4: battery consumption of optimization steps

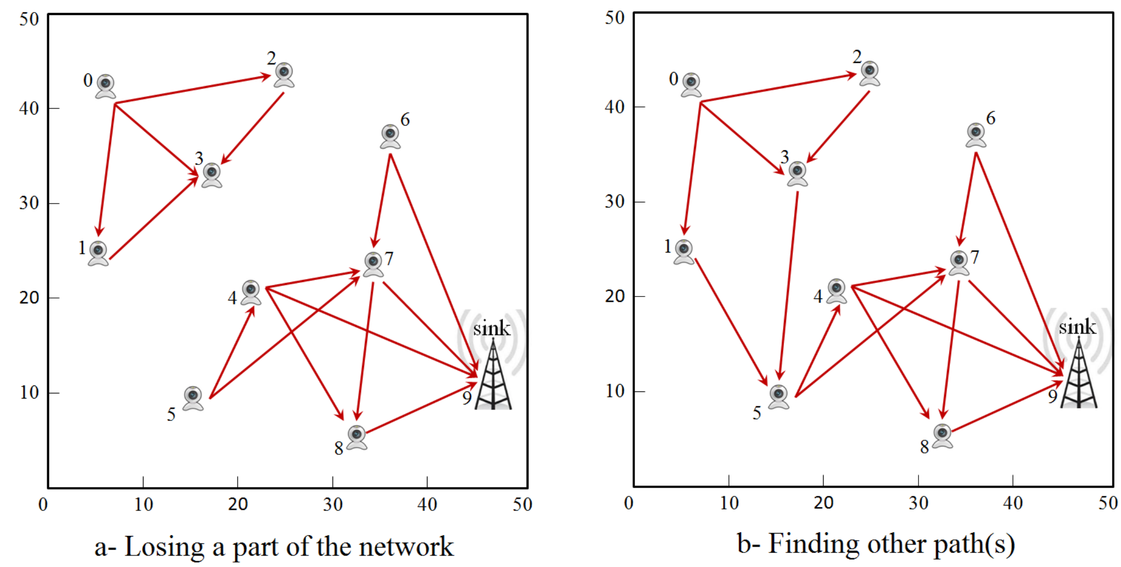


Fig. 7.5: Network model of the successive perturbation

7.4.3/ Activity duration of the optimization steps

The activity duration of the optimization steps refers to the required time till the convergence of the system. As the previous subsection, we choose the nodes with the highest activity duration, namely, node6, node8 and node1 for successive, uniform and gaussian perturbations, respectively, as well as node8 for the basic solution without perturbations. From figure 7.6, it can be observed that the solution that requires the highest duration is the one with the successive perturbation. As previously explained, this solution requires more iterations in order to ensure the convergence of the system, and thus, required more activity duration. It can also be observed that including the perturbations to the system requires non negligible activity duration compared to the basic solution.

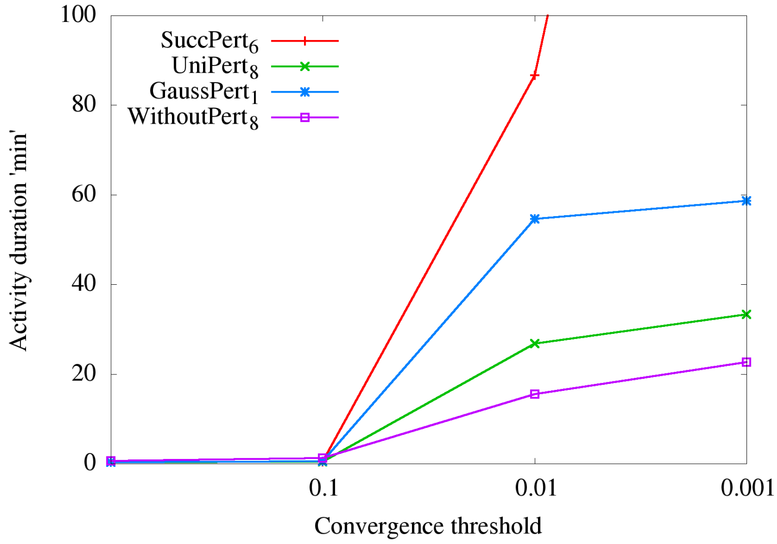


Fig. 7.6: Activity duration of optimization steps

7.4.4/ Node lifetime improvement

In this subsection, the node lifetime was calculated. From figure 7.7, it can be observed that our solution, with including the perturbations, efficiently improve the node's lifetime. In this figure, the nodes with the lowest lifetime improvement were selected, namely, node5, node1 and node1 for successive, uniform and gaussian perturbations, respectively. The improvement is about 5.14, 4.56 and 5.59 times for successive, uniform and gaussian perturbations, respectively, compared to the baseline approach without the optimization steps.

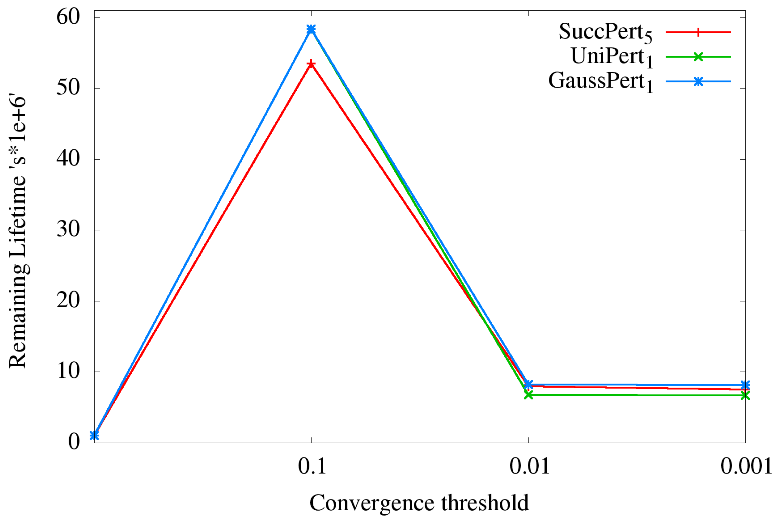


Fig. 7.7: Remaining lifetime after each convergence threshold

In order to push our evaluation further, we have studied the uniform perturbation solution, where the number of links were increasingly removed (referencing this by percentage in figures 7.8, 7.9 and 7.10).

Before going further, figure 7.8 shows the convergence of the system at every removed links percentage. This figure highlights also the moments when the perturbations occurs (*i.e.*, the peaks in figure 7.8). It should be known that these peaks concerns also the routing phase where the nodes verify the adequate number of paths required to send their data toward the sink node.

We can also observe that after the perturbations the system restabilizes and converges to the common variable q. As the previous evaluation, the system is considered to be completely functional when the convergence threshold T is equal to 10^{-2}.

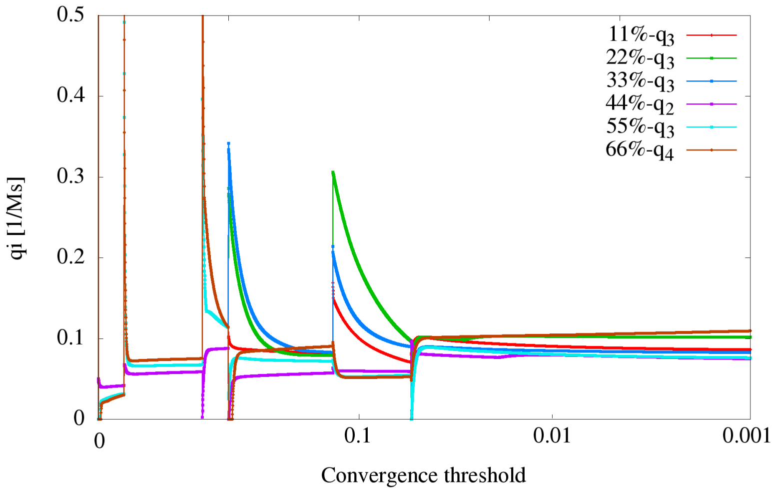


Fig. 7.8: System convergence

Figure 7.9 and figure 7.10 show the impact of the perturbation on the encoding power and data rate variables. After the perturbation phase, each node optimally allocates its resources. Let us mention that the nodes with more incoming links (namely, the intermediate nodes) have the lowest encoding power in order to preserve their energy for the routing phase (*i.e.*, transmission and reception steps).

Let us now discuss the main objective of this chapter, namely, the node's lifetime improvement while combining the two axes, namely, data processing and data routing axes. At this stage, the nodes with the lowest lifetime improvement were selected (namely, node3 when 11% of links were removed, node3 when 22% of links were removed, etc.). Figure 7.11 shows this improvement, it can be observed that there is a slight difference between the different experimentations. However, the experimentation with the highest number of removed links (namely, 66% of links have been removed) have also the highest node lifetime and hence the highest network lifetime. This can be explained by the fact that the latter sends much less data traffic compared to that it has(due to the luck of paths and the limited capacity of the existing paths). So that, it gains in network lifetime to the detriment of the video quality at the destination level.

Once the system is complectly functional (*i.e.*, all the nodes have converged) the optimization phase ends and only the sending of data will continue. Thus, following the steps described in section 7.3, we have evaluated our solution even after the optimization steps. Let us recall that, in this solution the incoming link capacity from node i to node j

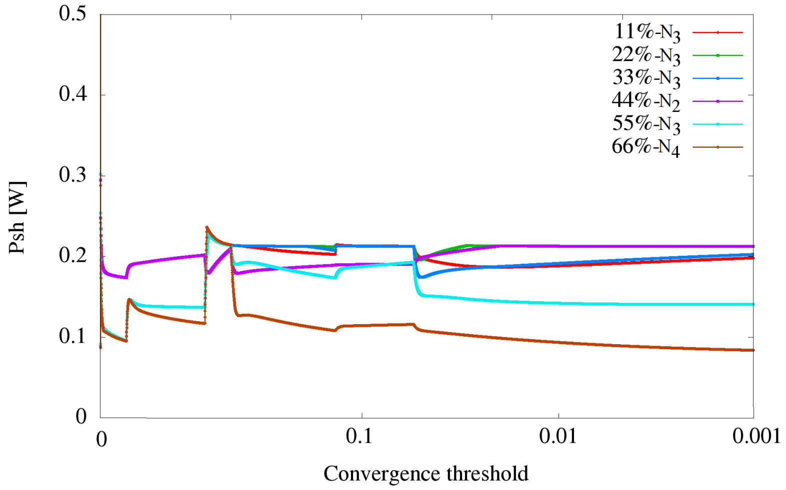


Fig. 7.9: Encoding power variation

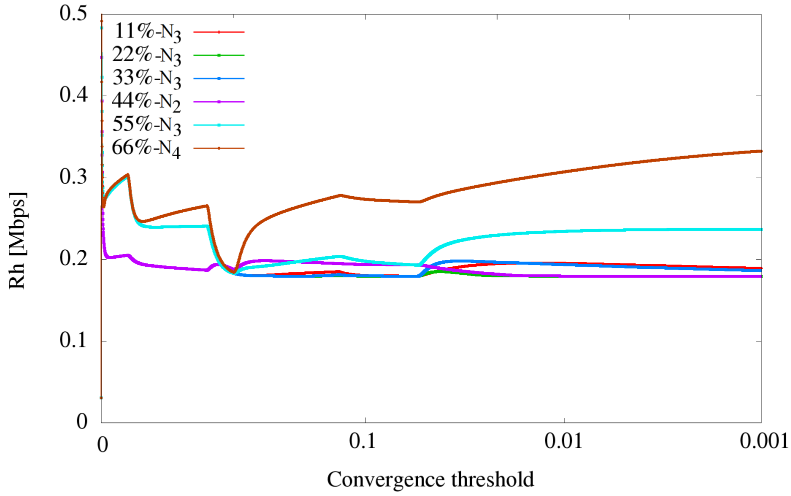


Fig. 7.10: The generated traffic by the source node

decreases with respect to the remaining energy of node j. Thus, after a certain period of time, the node j could no longer ensure the transmission of the incoming data from node i, and the latter have to find an additional path (with respect to the reliability) in order to reward the loss of link capacity.

Before going further, let us, firstly, show the convergence of the system. From figure 7.12, we can observe the convergence of the system with some peaks. The first peaks concern the routing phase where the nodes verify the adequate number of paths and the moments when the perturbations occur. The last peaks can be explained by the fact that the system returned to the optimization steps phase after the data sending phase (*i.e.*, one or more nodes require and have found an additional path(s)).

The main objective behind multiplying the incoming link capacity by the remaining energy of the receiving node is to save more energy. Thus, figure 7.13 shows the energy consumption of the nodes that consume the most energy over two solutions. The first solution (*i.e.*, *WithEnergy* in figure 7.13) is the one that takes into account the energy

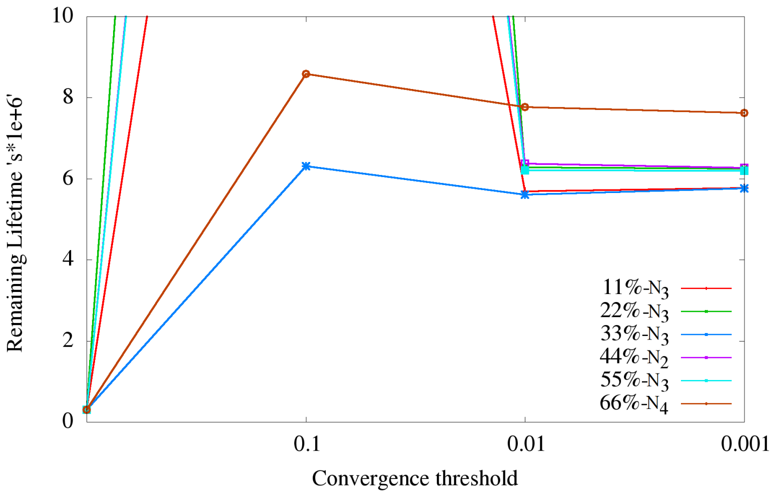


Fig. 7.11: Node's lifetime improvement

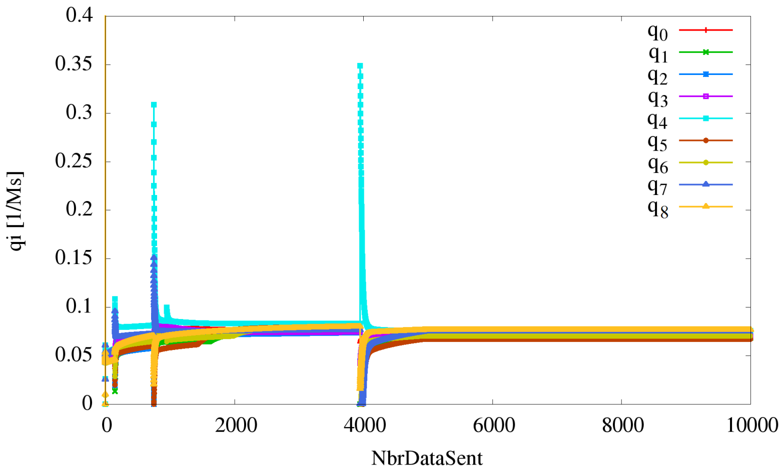


Fig. 7.12: Convergence of the system

of the intermediate nodes **during** and **after** the optimization steps phase (*i.e.*, the link's capacity is decreasing with respect to the remaining energy of the intermediate node), while the second solution (*i.e.*, *WithoutEnergy* in figure 7.13) considers the energy of the intermediate nodes **only during** the optimization steps phase. From this figure, we can observe that the first solution ensures more data transmission and can save until 25% of energy compared to the second solution.

Note that, this gain in term of energy is not without consequences. In fact, after a certain period of time the intermediate nodes could no longer ensure the data transmission of their incoming neighboring nodes, and these latter could no longer find an additional paths in order to ensure the video quality at the destination level. Therefore, the distortion of the transmitted data is highly affected as shown in figure 7.14. Thus, depending on the application requirements the first or the second solution can be chosen.

In order to better understand the impact of the distortion on the data, figure 7.15 shows this impact over different value of the distortion. Even though, in nowadays, it is possible to transform a heavily pixellated, low quality, image into a clear photo or a person or object

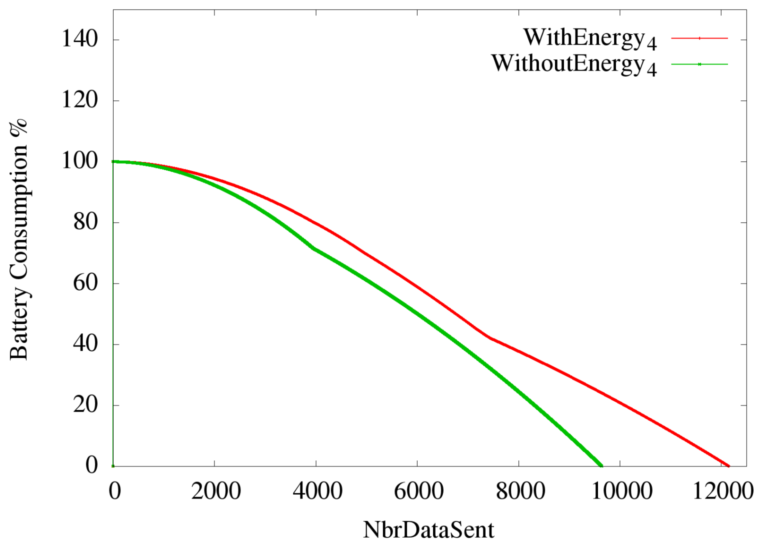


Fig. 7.13: Energy consumption comparison

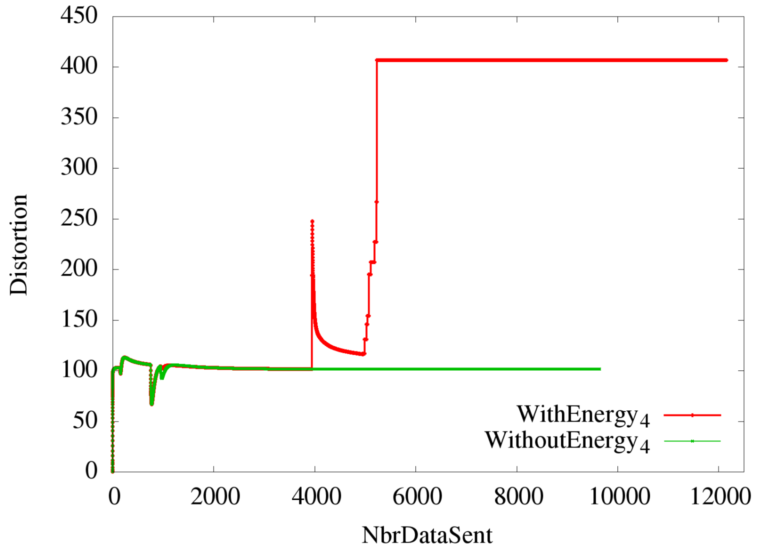


Fig. 7.14: Distortion comparison

as shown in [33], based on combining two artificial intelligence systems.

The aim behind the figure 7.16 and figure 7.17 is to show the rebalancing of the encoding power and the data rate during the first and second optimization steps phase. In fact, at the end of the first optimization steps phase, for the first solution, the encoding power of node 4 have been stabilized at $0.10299W$ and the data rate have been stabilized at $0.29018Mbps$ and thus to be used at the data sending phase. However, during the data sending phase the capacity of the incoming links of a given node have been changed (decreased), which require the nodes to find additional paths and thus return to the optimization steps for the second time. In the second optimization steps phase, the system takes into account the aforementioned changes and rebalances the two parameters to $0.15018W$ and $0.13716Mbps$ for the encoding power and the data rate, respectively. It can

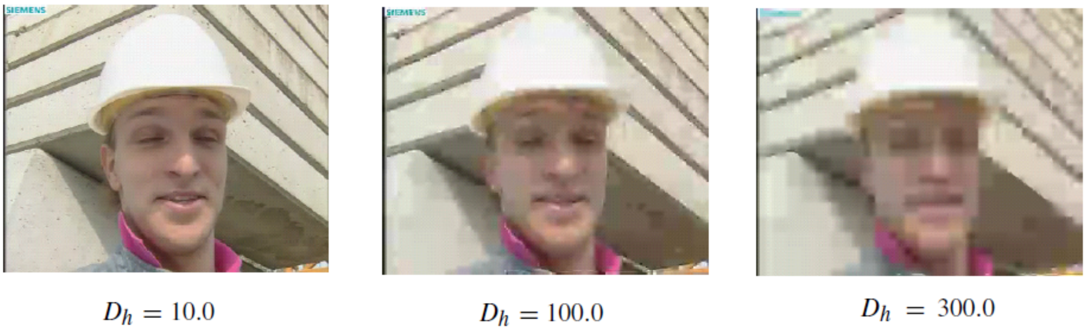


Fig. 7.15: Image distortion (heavily borrowed from [54])

be observed that the system has chosen to increase the level of compression, in order to decrease the number of bits to be transmitted, and thus to adapt the parameters of the data processing axis with the parameters of the routing axis.

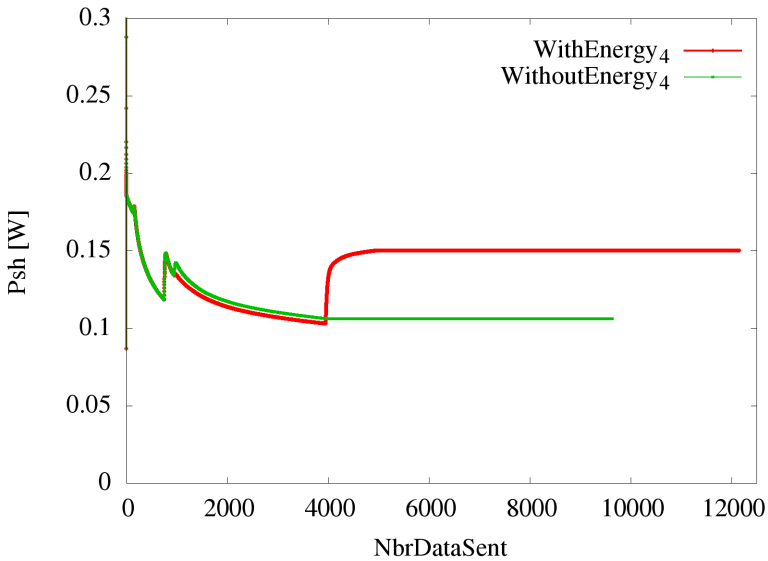


Fig. 7.16: Encoding power comparison

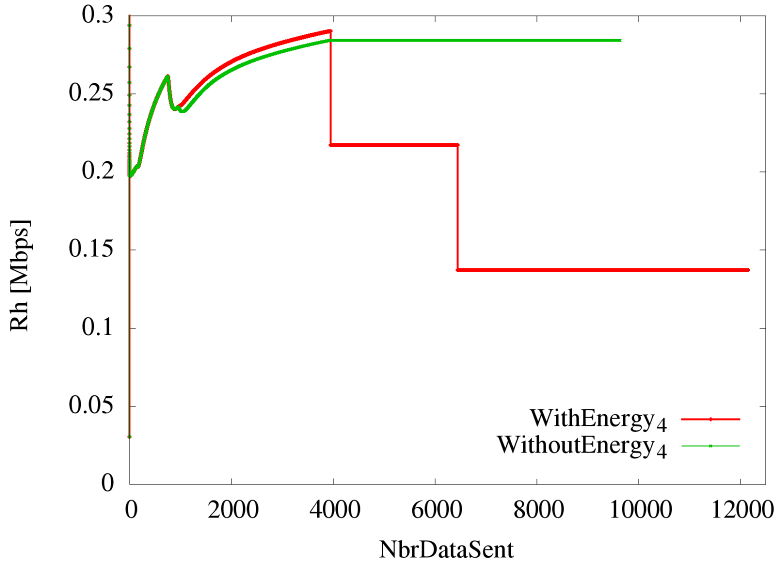


Fig. 7.17: Data rate comparison

7.5/ Conclusion

In this chapter, we have proposed a fully distributed solution that combines the two axes, namely data processing axis and data routing axis, while taking into account: **a)** the dynamic link's reliability, using probabilistic perturbations distribution and **b)** the dynamic link's capacity that was adjusted depending on the remaining energy of the forwarding nodes.

In order to save more energy, we have extended the proposed solution after the convergence of the system. In fact, once the optimization phase ends, only the data transmission will continue. In this stage, the incoming link's capacity of a given node will be decreased with respect to the remaining energy of the latter. The simulation results show that, with this solution we can save till 25% of the energy compared to the solution without considering the remaining energy of the intermediate nodes after the convergence of the system.

To the best of our knowledge, this is the first work that dynamically decreases the capacity of the incoming links depending on the remaining power of the concerned nodes.

III

CONCLUSION

8

Conclusion and Perspectives

8.1/ Conclusion

Wireless video sensor network is a new challenging domain. One of the most important issues is to achieve an optimal video data compression through an efficient resource allocation, while maximizing the overall network lifetime. However, the multimedia data is usually voluminous and delivering the compressed video data to the forwarding node poses an emergent demand, for simultaneously optimizing the video encoding and data routing performance in order to maximize the network lifetime.

In this manuscript, six main contributions related to our field of interest, namely, the network lifetime maximization in wireless video sensor networks, have been realized.

In chapter 2, we have started by realizing a theoretical state of the art. In the latter, we have examined the literature works where the main objective is to maximize the network lifetime in wireless multimedia sensor networks. Then, in analyzing this approaches, we could classify the existing works into two main axes: the data processing approaches and data routing approaches. We could also highlight which of the parameters are mostly used in one axis and ignored by the other one. This study allowed us to: **a)** position our own work in relation to the existing ones and **b)** determine the direction of our work in order to propose the efficient solutions that take into account the main parameters of the two axes.

In chapter 3, and in order to better understand the functioning of each axis and propose the efficient solutions, we have firstly started by the data processing axis, which means that the routing was considered as an input. The main challenge in this chapter was to optimally find a tradeoff between the compression level at the source node and the desired video quality at the destination level. To do so, a fully distributed approach was proposed, and the effectiveness of the proposed solution was proved by the simulation results.

Then, in chapter 4, we have extended our proposal by allowing it to handle a **dynamic change of links capacity**, in order to avoid both: (a) data loss (b) and low network connectivity. In other terms, we included additional constraints. To this end, a novel mathematical model is formulated considering both limited links capacity and limited transmission and reception powers. The proposed solution has shown its effectiveness in comparison to the literature approach (namely, the DQLM [49] approach).

After ensuring an optimal power/rate resource allocation that maximizes the network lifetime while respecting the desired video quality at the destination. Chapter 5 started tackling the second axis namely, the data routing axis. Thus, the first step was to show the impact of the routing protocols on the network lifetime. Consequently, this chapter, the behaviour of various routing protocols have been analyzed. These latter have been implemented as an add on to the fully distributed algorithm of the second chapter. The analysis was conducted on two different configurations. The results have confirmed that, the data routing and data processing axes are not independent and their interaction affects enormously the network lifetime.

From this point, the combination of the two axes has started. Chapter 6, firstly proved that the problem of choosing a single routing protocol among n routing protocols is NP-complete. Then the integration process was addressed by integrating the routing issue into the analytic model proposed in second chapter. The resolution of the latter is semi-distributed and can results in one-path, two-paths or three-paths from the source nodes to the destination (the number of the required paths can be expressed as an application parameter). However, the problem was divided into two sub problems, in which the resolution of the data processing axes goal cannot be achieved without the results of the data routing axis. Nevertheless, the resolution of the data routing axis problem (i.e., routing problem) did not consider any of the parameters of the first one.

Thus, in the second part of this chapter, a fully distributed solution was proposed. The latter respects both the optimal resource allocation and the reliable end-to-end delivery of multimedia data content. In this part, the routing axis goal cannot be achieved without the data rate and links capacity parameters, determined and updated by the data processing axis. On the other hand, the data processing axis goal cannot be achieved without the routing tables updated by the routing axis. The proposed solution allows: **a)** an end-to-end routing with local decisions at each video sensor node without end-to-end path discovery and maintenance and **b)** the choose of the sufficient number of paths needed to ensure a reliable data transmission and traffic distribution (the number of paths selected should respect the optimal data rate generated at each video node and links capacity).

Finally, chapter 7 proposed a fully distributed solution that takes into account the dynamic change of link's reliability (implemented using probabilistic perturbations distribution) and link's capacity (depending on the remaining energy of the forwarding nodes). The resolution of the optimization problem is fully distributed and can cope with dynamic topologies. In order to save more energy, this chapter extended the proposed solution after the convergence of the system. In fact, once the optimization phase ends, only the data transmission will continue. In this stage, the incoming link's capacity of a given node will be decreased with respect to the remaining energy of the latter. The simulation results have showed that, with this solution we can save till 25% of the energy compared to the solution without considering the remaining energy of the intermediate nodes after the convergence of the system.

8.2/ PERSPECTIVES

In this dissertation, the main focus was to maximize the network lifetime while finding a trade-off between the network resources and the desired video quality at the destination level. In this context, we have combined the most consuming axes in term of energy, namely, the data processing and data routing axes. Based on this combination, we have proposed an novel solution that takes into account the main parameters of each axis.

We give hereafter some possible directions that can follow our works:

- **Direction 1.** Depending on the application requirement, the solutions proposed for WVSN can cope with either large-delay WVSN application (e.g., environmental data collection), or small-delay WVSN application (e.g., nuclear center monitoring). In this thesis, the delay, in the large-delay applications, was considered by using the retransmission mechanism, since the main objective in this kind of application is the successful delivery of data. For the small delay applications, the delay was implicitly considered as follows: Firstly, it was tackled by using the multi path routing, in other terms, instead of sending the splitting packet one after the other, the existing paths can be used to transmit these packets simultaneously. Secondly, by choosing the shortest paths. Nevertheless, another direction of this dissertation is to consider the end-to-end delay. In fact, the latter should be also explicitly added as a constraint allowing the choose of the best existing paths with minimum delay.

- **Direction 2.** Indeed, discussing about applications that do not tolerate end-to-end delays, the mechanism for retransmitting the corrupted packets is no longer appropriate. As a result, an error correction mechanism at the destination level must be implemented.

- **Direction 3.** At the difference with traditional wireless sensor networks, where the sensing region of the sensor node is represented by a disk model, in the WMSNs, the multimedia sensors nodes may have a limited sensing region represented by a Field of View (FoV), usually represented as **a cone**. Due to this difference, coverage algorithms for traditional sensor networks can not be applied straightforwardly and efficiently in WMSNs.

  However, the proposed solutions in the literature for the different categories of coverage (namely, Target coverage, area coverage and barrier coverage) are invalid in some situations, such as a military camp that must be monitored all around to avoid any enemy intrusion. Thus, the $360°$ coverage should be addressed and an appropriate solution for wireless video sensor networks should be implemented. Therefore, considering the coverage problem into the proposed analytical model, to identify and form a set of closed peripheral covering sets where each of which forms a closed ring should be addressed in our future work.

- **Direction 4.** What about security? Multimedia data content is more disclosing compared to scalar data, and thus, the security of the multimedia content is crucial and inescapable task. Additionally, the secure of the multimedia data is much more complex compared to the scalar data due to the huge volume of the multimedia content, and this poses more challenges considering the resource limitation of the sensor nodes. Thus, combining the security axis with the two considered axes can be a promising direction of this work.

Personal Bibliography

Publications Related to the thesis

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