# SUM-RATE MAXIMIZATION AND DATA DELIVERY FOR WIRELESS SEISMIC DATA ACQUISITION SYSTEMS

BY

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# $\label{lem:decomposition} Dedication \\ \textit{To my parents and brothers for their endless support and love}.$

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# LIST OF ABBREVIATIONS

ACO Ant colony optimization

ADC Analog to digital converter

AMPSO Angle modulated particle swarm optimization

AS Ant system

BER Bit error rate

BP Binary programming

CDMA Code division multiple access

CSI Channel state information

DC Data center

DPSO Discrete particle swarm optimization

FD Full duplex

FDMA Frequency division multiple access

GP Geophone

GW Gateway

HD Half duplex

IoT Internet of things

IP Integer programming

MAC Multiple access channel

MMAS Max-min ant system

MSE Mean square error

NP Non-deterministic polynomial

PSO Particle swarm optimization

QoS Quality of service

SA Simulated annealing

SIC Successive interference cancellation

SINR Signal to interference plus noise ratio

SNR Signal to noise ratio

SQP Sequential quadratic programming

TDMA Time division multiple access

TF Time fraction

# THESIS ABSTRACT

NAME: Abdullah Othman

TITLE OF STUDY: Sum-Rate Maximization and Data Delivery for Wireless

Seismic Data Acquisition Systems

MAJOR FIELD: Telecommunication Engineering

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Traditional seismic acquisition systems suffer from a number of disadvantages related to using telemetry cables as a means of data transmission. To solve these problems, the scientific community is considering transforming the seismic acquisition system into a wireless system. In this work we consider the problem of maximizing the information theoretic sum-rate of the geophones in a seismic acquisition system. We assume successive interference cancellation decoding at the gateway nodes and use Shannons capacity bounds. We propose various integer programming algorithms that search for the optimal set of geophones to be decoded at each of the gateways. The proposed optimization algorithms are simulated and compared, where it is shown that the ant system achieves the highest sum-rate in a short time compared to other algorithms. Furthermore, we study the data delivery

from the gateways to the data center. In this stage, we differentiate between two types of the gateways based on the length of the buffer. For small-size buffers, two problems are proposed and solved. The first problem considers the minimization of the total power of the gateways and the second problem considers power fairness between the gateways. For large-size buffers, we propose a problem to maximize the weighted-sum rate of the gateways. For the three problems, convexity is studied and the optimal power distribution and decoding order at the data center are obtained.

### ملخص الرسالة

الاسم الكامل: عبد الله عثمان

عنوان الرسالة: زيادة معدل المجموع للحدّ الأقصى و تسليم البيانات لنظام تحصيل البيانات الزلزاليّة اللاسلكيّ

التخصص: هندسة الاتصالات

تاريخ الدرجة العلمية: مايو ٢٠١٨

تعاني أنظمة تحصيل البيانات الزلزالية من عددٍ من العيوب المتعلقة باستخدام كابلات القياس عن بُعد كوسيلةٍ لنقل البيانات. لحل هذه المشاكل، يفكّر المجتمع العلميّ في تحويل نظام التحصيل الزلزاليّ إلى نظام لاسلكيّ. في هذا العمل، نتعرّض لمشكلة تحقيق أعلى قدرٍ من المعلومات لمعدل المجموع النظريّ للسمّاعات الأرضيّة في نظام التحصيل الزلزاليّ. نفترض فكّ تشفير إلغاء التداخل المتتالي عند نقاط البوابة و نستخدم حدود شانون للسعة. نقترح العديد من خوازميّات البرمجة الصحيحيّة التي تبحث عن المجموعة المثلى من السمّاعات الأرضيّة التي سيتم فكّ تشفيرها عند كل بوابةٍ. يتم محاكاة خوارزميّات التحسين المقترحة و مقارنتها، حيث يتبيّن أنّ نظام النمل يحقّق أعلى معدل مجموع في وقت قصيرٍ مقارنة بالخوارزميّات الأخرى. علاوةً على ذلك، نبحث تسليم البيانات من البوابات إلى مركز البيانات. في هذه المرحلة، نفرّق بين نوعين من البوابات على أساس طول المخزن المؤقّت. بالنسبة للمخازن المؤقّة صغيرة الحجم، يتم اقتراح مسألتين و حلهما. تدرس المسألة الأولى التقليل من الطاقة الإجمالية للبوابات، و تدرس المسألة الثانية عدالة الطاقة بين البوابات. أما بالنسبة للمخازن المؤقّة كبيرة الحجم، نقترح مسألةً لزيادة معدل المجموع الموزون المؤقة و على ترتيب فك التشفير في مركز البيانات.

### CHAPTER 1

# **INTRODUCTION**

Driven by the huge demand of the global oil market, gas companies are constantly looking for potential new oil wells. This requires the research community to look for viable solutions for some of the disadvantages that traditional acquisition systems have, and to continuously improve the performance through high quality scientific investigation. Wireless technology is a promising tool to solve some of the cost and maintenance problems that are caused by cabled traditional acquisition systems. The industrial sector and the scientific community are pushing towards the replacement of cables by wireless technologies that are expected to improve and solve many of the problems currently faced. In this chapter a general background on the seismic acquisition system and on several topics related to the thesis is presented. Secondly, the contributions of the thesis are highlighted. Finally, the thesis organization is explained.

## 1.1 Background

We start with a general overview of a practical seismic acquisition system and then by introducing its various components and their functions. After that, some necessary background is presented about several areas related to concepts from communication engineering and optimization theory. This covers mathematical subjects such as multiple access channel (MAC), integer programming and convex optimization. It also covers other areas in communication engineering such as relaying networks.

#### 1.1.1 Seismic Acquisition System

is used to probe potential natural areas that are rich with crude oil. To achieve that, a form of seismic energy is thrust into the surface of the surveyed area. A seismic source generates controlled seismic waves that travel through multiple layers of ground. Some of these waves are reflected back and recorded by special sensors called geophones (GP). A GP tracks the ground movement and converts it into electric pulses (voltage) that are recorded. This data about interior geological layers are either transmitted instantaneously to the data center (DC) for collection and processing, or possibly stored in buffers for a period of time before retransmission.

To efficiently transmit data from the GPs to the DC, traditional seismic acquisition systems have employed telemetry cables. Although efficient in reliability, these cables are a burden in terms of cost and weight. With surveys growing larger

in scale, costs of deployment and maintenance become proportionally higher. Furthermore, environments with complex terrains render deployment of cabled systems impractical. Hence, there is an increasing trend in oil exploration companies to move to wireless technology to avoid these challenges.

Wireless GPs are deployed in a grid-like network to cover the whole survey area whereas wireless GWs are deployed between the GP lines. The purpose of GWs is to collect data from the GPs, possibly store them for some time, and then forward the collected data to the DC for processing [1]. A typical land survey deploys 20,000 to 30,000 GPs over a large area in the order of 20 km<sup>2</sup>. A GP equipped with a 24-bit analog-to-digital converter (ADC) generates sampled data at a rate of 48 kbps. The aggregate data rate for a typical survey can be about 4.32 Gbps, when all the GPs are active. A cross section of an orthogonal geometry survey is shown in Fig. 1.1, where two GWs are spread between the source and receiver lines to harvest the data from the GPs. GWs may have some buffering capability to store the collected data for some time. After that they are sent to the DC for processing.

## 1.1.2 Multiple Access Channel

A MAC channel is one where several users share the medium for transmission to a single destination. Specifically, a Gaussian MAC is characterized by two or more users sending simultaneously over the channel as follows:

$$Y_i = X_{1i} + X_{2i} + Z_i (1.1)$$

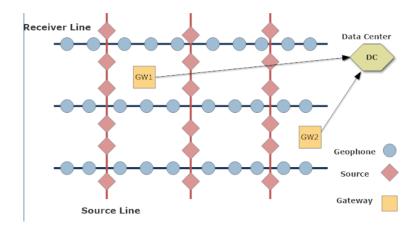


Figure 1.1: A cross-section of an orthogonal geometric wireless acquisition system where  $Z_i$  is Gaussian noise with variance  $N_0$  and i is the time index [2]. A capacity region is the set of achievable user rates defined by the following inequalities:

$$R_{1} < \log_{2} \left( 1 + \frac{P_{1}}{N_{0}} \right)$$

$$R_{2} < \log_{2} \left( 1 + \frac{P_{2}}{N_{0}} \right)$$

$$R_{1} + R_{2} < \log_{2} \left( 1 + \frac{P_{1} + P_{2}}{N_{0}} \right)$$
(1.2)

where  $P_i$  and  $R_i$  are the power and rate of User i, respectively. We adopt a method of decoding at the destination known as successive interference cancellation (SIC) [3, 4, 5]. In SIC, the destination decodes the users successively by first decoding one of the signals of the users, and then subtracting it from the sum-signal. By doing so, the interference from the previous user is subtracted. Thus, the first user to be decoded sees interference from all subsequent signals and the last user will enjoy an interference-free rate according to the bounds in Eq. 1.2. Fig. 1.2 shows the multiple access region for two users, where the line between the points

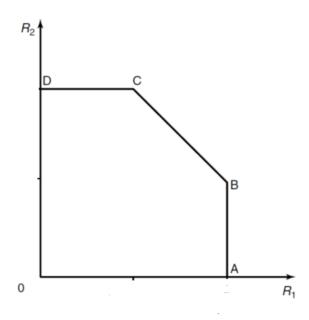


Figure 1.2: A multiple access region for two users

B and C is the line of maximum sum-rate. Point B can be achieved by successively decoding user 2 then user 1, and point C can be achieved by following the opposite order. The points on the line can be achieved by time sharing between the two decoding order combinations.

# 1.1.3 Integer Programming

(IP) is a form of mathematical optimization where some or all of the variables are integers. If the variables are allowed to take only 0 or 1, the problem becomes knows as binary programming (BP) where the value of the variable represents a decision. A value of 1 represents a Yes decision and a value of 0 represents a No decision. IP problems belong to non-deterministic polynomial time problems (NP). NP problems is known for being difficult to solve in a limited time. For many IP problems, the techniques used aim at finding a guess of the optimal

solution rather than finding the optimal solution. Some of the methods used to solve integer programming problems are:

#### 1. Branch and bound:

where the search space is explored by dividing it systematically into branches. The algorithm tests the candidate solutions against upper and lower bounds on the optimal solution. The algorithm keeps repeating the process and discarding the branches that do not satisfy the bounds until it arrives at an acceptable solution.

#### 2. Heuristics:

are problem-specific low-complexity search protocols that provide a suboptimal solution by exploring the search space in a fast way. Heuristic algorithms move in the search space by applying local changes to the proposed solution and choosing a candidate solution. It repeats the process until an acceptable solution is reached or the computational time has elapsed.

#### 3. Metaheuristics:

are high-level algorithms that are applicable on a wide-range of problems. They are generally used to solve complex problems where it is hard to develop a specific algorithm [6]. Many of the metaheuristic algorithms are inspired by observations from social science, evolution and nature. Examples of metaheuristics include tabu search, simulated annealing and swarm intelligence algorithms.

### 1.1.4 Convex Optimization

is a sub-field of optimization theory which covers a wide range of problems. A convex optimization problem follows the general form

$$\min f(x),$$
 subject to 
$$g_i(x) \leq a_i, \forall i,$$
 
$$h_j(x) = b_j, \forall j, \tag{1.3}$$

where f(x) and  $g_i(x)$ ,  $\forall i: \mathbb{R}^n \to \mathbb{R}$ , are convex. A convex functions,  $g_i(x)$  satisfies the linear or affine equality constraints,

$$g(\alpha x + (1 - \alpha)y) \le \alpha g(x) + (1 - \alpha)g(y)$$

for all  $x, y \in \mathbb{R}^n$  and  $\alpha \in \mathbb{R}$  where  $0 \le \alpha \le 1$ . There are no general closed-form solutions for convex optimization problems. However, some efficient algorithms have been developed to solve them efficiently. For example, the interior-point methods is a practical approach for solving convex optimization problems with reliable accuracy. Also, sequential quadratic programming algorithm (SQP) is known to reliably solve convex optimization problems [7]. Any problem that can be formulated as a convex optimization problem is possible to be solved using convex optimization tools. Therefore, it is a challenging task to recognize and formulate the optimization problem in a proper form.

#### 1.1.5 Relaying Network

is a class of cooperative networks that utilize intermediate relays between the source and destination to facilitate the transmission process. It has been a hot topic of research recently due to its advantages such as diversity and coding gains. It is predicted to be employed in some technologies associated with fifth generation (5G) cellular networks. There are generally three relaying strategies:

#### 1. Amplify and forward:

where the relay amplifies the received signal from the source and forwards it without decoding.

#### 2. Decode and forward:

where the relay decodes the signal received from the source. It then encodes it again and forwards the data towards the destination. Decode and forward strategy mitigates errors as it prevents erroneous signals from reaching the destination. It does so by discarding the data that are in error.

#### 3. Compress and forward:

where the relay uses compression of the received signal, before it forwards the signal towards the destination.

Decode and forward relaying is adopted in this work. Furthermore, there are two main classes of relaying networks: conventional relaying and buffer-aided relaying networks. Conventional relaying networks prompt the relays to transmit their data without waiting for future sessions. However, buffer-aided relaying networks

allows the relays to keep the data and thus make use of the channel state. So when the channel gain is large, the relay can increase its rate by sending at that time slot.

### 1.2 Thesis Contributions

In this section, the contributions of this thesis are presented and described.

#### 1. System modelling,

The seismic acquisition system is modelled as a two stage communication system. The first stage shows a multiple GPs sending their data to a few GWs. These GWs are equipped with buffers to store the received data. In the second stage, the GWs send their data to the DC for further processing. This modelling allows us to study some theoretical aspects of the seismic acquisition system, e.g. achievable rates and maximum sum-rate.

#### 2. Maximization of the sum-rate,

The problem of maximizing the sum-rate of the GPs in the first stage is studied and formulated as an integer programming problem. By letting each GW select a set of the GPs to be decoded using SIC, the problem is solved using various metaheuristic algorithms.

#### 3. Convergence of metaheuristic algorithms,

The problem of stagnation and slow convergence of the metaheuristic algorithms is studied. Ant colony optimization algorithms are reported to suffer

from slow convergence especially when the search space gets too large while the computational complexity of the algorithm is limited and incomparable to it. Hence, our adaptation of the algorithms parameters show that convergence speed is boosted and results are improved.

#### 4. Adapting simulated annealing algorithm to binary case,

The simulated annealing metaheuristic algorithm has been originally introduced to tackle continuous optimization problems. Here, we develop a low-complexity discrete version of the algorithm that works on the binary vectors. The proposed algorithm is shown to produce comparable results to the optimal solution provided the computational complexity is large enough.

#### 5. Data delivery to the DC,

The transmission of data from the GWs to the DC is considered. Two types of buffers are assumed at the GWs. Three optimization problems are formulated based on the size of the buffer and the objective of each problem. Small-size buffers at the GWs are considered first and two problems are proposed. The first problem is to minimize the total power expenditure of the GWs that is needed to deliver the data to the DC. The second problem is to minimize the maximum power of the GWs. The third problem is proposed for large-size buffers at the GWs. The third problem is the maximization of the weighted-sum rate of the GWs. Using convex optimization tools, the problems are solved and results are shown.

## 1.3 Thesis Organization

Chapter two presents the literature survey in three subjects. It covers the milestones achieved in seismic acquisition system, the relaying networks and the MAC.
Chapter three addresses the first stage in a seismic acquisition system. We present
the system model, formulate the problem mathematically and propose various
metaheuristic algorithms to solve it. Then, the simulation parameters and the
results are presented. Chapter four addresses the second stage in the seismic acquisition system. We present three problems based on the length of the buffer at
the GWs, and based on the objective function. Then, the methodology to solve
the problems is demonstrated, and results are presented. Chapter five presents
the conclusion and future works. Based on our work, our findings are summarized
and possible extensions and future works are suggested, which can be built upon
this work.

### CHAPTER 2

# LITERATURE SURVEY

A review of some of the work done in the literature about seismic acquisition system and relaying networks is presented in this chapter. We start by reviewing some of the literature done in the seismic acquisition system. A review of the literature of the relaying networks follows. After that, some of the work done on the MAC is presented. The relaying networks section is divided into conventional relaying networks, which do not employ buffers, and the buffer-aided relaying networks. Finally, the chapter is concluded with the thesis motivation that is partly based on the literature survey.

## 2.1 Seismic Acquisition System

Driven by the trend towards wireless seismic surveying, several authors studied cable-less surveys and wireless architectures in the literature. Savazzi et al. [8] proposed using ultra-wide band wireless technologies in land seismic acquisition systems, where a hierarchical architecture-based, short-range and long-range com-

munications were developed for two-stage data delivery. For all the wireless nodes in the system, it is required that they self-localize and organize into clusters that deliver data using compress and forward relaying. Freed [9] argued for nodal systems where GPs receive seismic data continuously and store them for future retrieval. He argues for using GPs that have exceptional battery size. This solves the challenges associated with real-time data acquisition especially with substantial number of channels. It also eliminates the need for continuous visits to the surveying site for maintenance and supervision. However, it does not address issues other than power consumption and communication such as the need for delivering data in real-time or near real-time. Ellis [10] maintained that a fully real-time acquisition system is not possible. He rather argued for a hybrid system that combines cable and cable-less acquisition systems. The reasons behind his claim are primarily the battery limited life and the need for troubleshooting. However, he does not fully differentiate between a real-time acquisition system which still can be supervised by professionals for issues related to battery depletion and troubleshooting, and between a fully autonomous system that is completely free of manpower.

Addressing the autonomous operation of the seismic acquisition system, the authors in [11] suggest utilizing the internet of things (IoT) technology to monitor oil and gas wells with reliable efficiency. Smart devices based on IoT can sense pressure, temperature and various other important parameters and relay them to the DC. This is more promising than the conventional wired and wireless acqui-

sition systems as it guarantees efficiency and timely data delivery. Furthermore, predictive measurements can be taken to prevent failures of equipment and initiate timely maintenance. Peebler [12] expects that the shale will play a major role in shaping the oil market and the technologies to be deployed as it can change the view on solutions to global warming. By 2020, he expects that the advances in computing technology will greatly affect any future seismic acquisition technology. Moore's Law will be substituted with a new magnitude of computing power which will change how processing of information including seismic interpretation is done. He also expects wireless real time systems to completely replace cable systems in order to reduce operational costs and increase the efficiency of these traditional systems. Zhong et al. [13] designed a prototype of a wireless acquisition system that is based on three different structures. The first is a network structure based on IEEE 802.15.4 standard to operate between the GPs and GWs. This structure has low power and low speed requirements to accommodate the capabilities of the GPs. The second is a structure based on IEEE 802.11b/g standard and it works between the GWs and DC. This structure is to ensure high data rate from the GWs towards the DC, and the third structure is an interface between the acquisition system and upper applications.

Tian et al. [14] proposes using global positioning system GPS to synchronize the work of all the channels in a wireless seismic acquisition system. Since every GP is doing sampling at its own time and then transmitting the data, there is a need for synchronization as this directly affect the output of the seismic system. The

proposed method can synchronize up to 1024 channel system, providing efficiency for the collecting, storage and transfer of seismic data. Savazzi and Spagnolini [15] emphasize the disadvantages of using cables in a high-density acquisition system. Furthermore, the authors list some technical requirements for a wireless GP to guarantee data delivery and self-localization with minimal power expenditure. A hierarchical centralized system is designed based on two levels of hierarchy. The authors predict that the telecommunication industry is mature enough to produce a wireless system that is ready for deployment in near future.

# 2.2 Relaying Networks

Cover and El Gamal first studied the discrete and memoryless, additive white Gaussian channels in [16]. Lower bounds on the capacity are formulated and derived. Three different random schemes are analyzed: facilitation, cooperation and observation [16]. In facilitation, relay facilitates transmission of the message while trying to induce as little interference as possible. In cooperation mode, the relay fully decodes the arriving signal and retransmits it again to the destination after re-encoding the signal. However, in observation scheme, the relay decodes a quantized version of the message, using source coding with side information.

Several selection cooperative relaying schemes were developed and analyzed in [17]. These relaying schemes combat fading generated by multipath propagation. The proposed protocols fall under two categories: fixed and incremental relaying. Fixed relaying includes amplify-and-forward and decode-and-forward schemes.

Amplify and forward relaying scheme amplifies the received message at the relay and then retransmit it to the destination, while the decode-and-forward scheme decodes the received message, re-encodes and then retransmits it to the destination [17]. The incremental relaying exploits limited feedback from the destination and it allows relaying only when necessary. It was found that for all schemes proposed full diversity order was exploited except for the decode-and-forward scheme.

Multiple input multiple output systems, also known as MIMO, achieved diversity gains making it attractive in communication. However, due to some obstacles, only single antenna mobiles are used. Cooperative communication emerged creating new possibilities. It can create a virtual MIMO system where single-antenna mobiles can share their antennas to increase the order of diversity. Signal attenuation can be variable in a transmission path, which leads to the phenomenon of fading. By transmitting independent copies of the signal, one can combat the disastrous effects of fading. This method is known as spatial diversity.

#### Conventional Relaying

These networks do not utilize buffers to store the received messages from the source. That makes a predetermined schedule for transmission and receiving inevitable. In [18], a multi-relay network is considered. Each relay is equipped with multi-antenna. Two different criteria were considered. The objective of the first

criterion is to maximize the SINR of the worst stream at the output of the receiver subject to source and relay transmit power constraints. The second criterion aims at optimizing the source and relay transmission powers with a certain quality of service (QoS) constraint. Both problems are nonconvex and were solved using iterative alternating techniques [18].

A bidirectional relaying scheme is analyzed in [19]. Two users send their information using an intermediate relay. Assuming channel state information at the transmitter (CSIT) is not available, the users attempt transmission with a fixed rate. Each node has one of three possible states: transmit, receive or silent mode. With the goal of maximizing the total sum of throughput, protocol is devised where the channel state information at the receiver (CSIR) is used to attain that goal. This protocol assigns a certain state to each node [19]. In addition to the conventional relaying scheme, RF energy harvesting was proposed in [20]. In this system, the source harvests energy from the relay, and then utilizes that energy in transmission to the destination. The time fraction (TF) the information transfer and the power transfer occupy changes from one fading state to the other. The goal is maximizing the achievable average data rate using two protocols:

- 1. Joint optimal power allocation and TF allocation.
- 2. Optimal power allocation with fixed TF.

The two protocols are found to achieve similar data rates, because the harvested power at the source is small [20]. Equipping the relays with buffers added a degree of freedom to the network. Whereas in conventional relaying networks a

certain relay should transmit following its receive interval, now more utilization of the opportunities offered by best channel state information is possible. Next, work related to buffered-relaying networks is presented.

#### **Buffer-Aided Relaying**

The literature review for the buffered-relay section is divided into three groups:

- 1. Single-Source Single-Relay networks.
- 2. Single-Source Multi-Relay networks.
- 3. Multi-Source Multi-Relay networks.

A simple network of a single source, a half-duplex (HD) relay and a destination is considered in [21]. A protocol that chooses a single link in a certain time slot is developed. The selection is based upon the instantaneous CSI at a given time. Two interesting cases are studied considering the delay. For the delay-unconstrained case, optimal relay selection policy is derived, the corresponding throughput is obtained and an optimal power allocation protocol is developed. As for the delay-constrained case, it is proposed that the buffer of the relay is starved by using a link selection policy that is suboptimal. And the corresponding average delays upper bound is derived. The results show that the proposed schemes achieve gains compared with conventional relaying schemes as well as buffered-relaying schemes that employed fixed schedule of transmission and reception [21]. The same network is reconsidered in [22], but here CSI is considered not available always. Two

cases are studied. In the first one, it is assumed both the source and the relay dont have CSI. Thus, both transmit with fixed-rate. In the second case, only the source doesnt have CSI, while the relay enjoys knowing CSI. So, the source transmits with a fixed-rate, while the relay transmits with an adaptive rate. For both cases, and when the delay is not a constraint, the selection protocol that optimizes the throughput is derived, by selecting the link which has the maximum instantaneous SNR. For the delay-constrained case, selection protocols are derived that achieve a pre-defined average delay [22]. For the fixed-rate scheme, a diversity gain of two is achieved subject to an average delay constraint of at least four time slots. Considering the mixed-rate case with average delay of E[T] time slots, a multiplexing gain of  $r = 1 - \frac{1}{2E[T]}$  is reported.

A bidirectional network of two users and an intermediate relay equipped with a buffer is considered in [23]. The objective is sum-rate maximization. In this network, four point-to-point transmissions are possible, between each user and the relay and vice versa. Also, a multiple access mode from both users to the relay and a broadcast mode from the relay to the users are possible. All transmission modes are adaptively used based on the instantaneous CSI of all the links. Thus, the relay is equipped with two buffers, for each user. Given a total average power budget, a joint optimization is developed for the relay selection and power allocation based on the instantaneous CSI per each time slot to maximize the sum-rate. It is reported that gains at low SNR due to power allocation, and at high SNR due to adaptive mode selection were achieved [23].

A full-duplex (FD) relay is assumed between the source and destination in [24]. The relay is equipped with a buffer. And three models are investigated: A conventional FD relay without a buffer, a FD relay with unlimited buffer and a FD relay with limited buffer. Throughput expressions are derived. For the buffered FD relay, the source transmits to the relay at a certain time slot, and the relay may or may not advance it to the destination based on the R-D link quality. If R-D link is bad, the relay can store the packet into its buffer and advance it later when the channel quality is suitable. This is obviously different from other conventional FD relaying schemes. Results show that buffered FD relaying achieves better throughput compared with conventional FD relaying [24].

A single HD relay with a buffer is considered in [25] with the aim of improving the capacity of the network. Two buffering relay techniques are introduced: fixed and dynamic. As the memory of the buffer and the SNR change, throughput, packet average delay and information loss are investigated. The dynamic relaying model has lower average delay than the fixed relaying model. Moreover, the dynamic relaying model gives a capacity that converges toward the ergodic capacity of a fast fading channel. The resulting behavior is attained as the buffer size grows infinitely large. However, with a moderate size buffer, the asymptotic behavior of the capacity can be achieved [25].

Max-max relay selection (MMRS) protocol is proposed in [26]. It chooses the best relays for transmission and receiving based on the channel links qualities. So, that the relay chosen for reception can store the packet received in its buffer and advance it later when the channel is good. This protocol is implemented under the assumption that relays buffers are neither empty nor full. For finite buffers, however, this assumption may not hold. Thus, another protocol is proposed which is a hybrid protocol between MMRS and a conventional relaying protocol, called best relay selection (BRS). In BRS, the best relay is chosen for transmission and receiving, at two consecutive time slots. The outage probability is studied and it is found that all proposed schemes give the same diversity gain as conventional BRS scheme, but with improved coding gain. More precisely, the hybrid protocol achieves a gain of 3dB over BRS, for a moderate buffer size of 30 packets, as the number of relays increase [26]. It is concluded that buffers add more flexibility to cooperative diversity systems.

In the network of N relays assumed in [27], a single relay is active at a time. New achievable average rates for this network are presented. As reported, still the capacity of the network is unknown. And the capacity region is not derived in [27]. However, a protocol is proposed to increase the achievable average rate given that a certain relay is chosen for reception or transmission. But this protocol introduces an unbounded delay. Another protocol bounds the average delay but at the expense of a drop in the maximum achievable average rate. Also, some centralized and distributed implementations of the proposed protocol are studied. It shows that the proposed protocols do not need additional resources for CSI acquisition than does the conventional relay selection protocols.

A diamond network comprised of a source, two HD relays and a destination, is

considered in [28]. There are four transmission modes. Each mode is linked to which relay is sending or receiving. The source either broadcast two codewords to both relays at the same time. The two relays might in another transmission mode transmit to the destination simultaneously. In the two other modes, one relay is transmitting to the destination while the other relay is receiving from the source, simultaneously. These two cases will introduce interference from the transmitting relay to the receiving relay. The optimal transmission mode selection scheme is derived with the aim of maximizing the data rate arriving at the destination. This optimal selection policy introduces unbounded delay. So, another delay-bounded protocol is derived. It is found that at an average delay of four time slots, the delay-bounded protocol attains data rates close to the optimal protocol at the expense of infinitely large delay [28].

Space full-duplex max-max relay selection (SFD-MMRS) protocol is proposed in [29]. Mimicking FD relaying, while utilizing HD relays, it allows the activation of different relays for reception and transmission concurrently. The interference between the relays is assumed negligible due to geographic isolation. The inherent deficiency in spectral efficiency for HD relays is addressed with SFD-MMRS. So, enhanced results in both outage probability and throughput are obtained. Capacity is studied in the adaptive rate transmission case, where the nodes acquire instantaneous CSI and are assumed to transmit with capacity achieving rates. Also, outage probability is studied using the fixed rate transmission case. In the fixed rate transmission, nodes are assumed to know only the statistical CSI and

thus transmit with a prior known fixed rate. Furthermore, full diversity order is achieved and large SNR gains are obtained. The protocol is shown to be superior to other protocols that employ only one relay at a certain time slot, i.e. one relay either transmits or receives. Comparison between BRS and MMRS illustrates this point. For any number of relays, SFD-MMRS achieves more than twice the capacity obtained by employing BRS, which is a conventional relaying protocol. Outage probability analysis shows that the protocol attains a diversity gain of N, for a system of N relays. Also, the coding gain is better than that of MMRS and BRS [29].

Many subsequent works adopted the same strategy of [29] where two different relays active at the same time, one transmitting to the destination while the other receiving from the source. In [30, 31, 32, 33, 34], inter-relay interference (IRI) is addressed as a problem to mitigate. Interference cancellation at the receiving relay is used in [30] and the selection protocol is derived such that the average capacity is maximized. Power adaptation is used in [35] to cancel the IRI. A protocol that minimizes the total power expenditure at each time slot under the interference cancellation condition is derived. Outage probability and average throughput are tested in comparison with previous schemes in the literature. Multiple antennas are assumed at the relays in [32, 33, 34]. Various beamforming techniques are used to mitigate the IRI. Two beamforming-based protocols are proposed in [32]. SINR-based and zero-forcing beamforming based (ZFBF). ZFBF-based protocol achieves average capacity that approaches the one where IRI is neglected,

as the number of relays and antennas increase. Minimum-variance beamforming (MVBF) is used in [33] to suppress the IRI. The proposed protocol selects two relays in each time slot, for transmission and reception, so that SINR is maximized. Throughput, outage probability and symbol error rate (SER) are investigated for evaluation and comparison with literature. A weighted sum-rate maximization strategy is proposed in [34] to address and mitigate IRI. Assuming adaptive rate is employed in source-to-relay and relay-to-destination links, an optimal scheme that uses iterative algorithms is proposed for selection of relays. Also, several other sub-optimal beamforming schemes are proposed to maximize the weighted sumrate while reducing the computational complexity. Results show that the optimal, zero-forcing and minimum mean square error BF-based schemes asymptotically approach the IRI-free upper bound while increasing the number of relays and/or antennas [34]. A hybrid protocol is proposed in [31] where the total energy expenditure is optimized for each time slot under an interference cancellation scheme. Markov chain is used to model the evolution of the buffers and study outage probability and diversity of the derived protocol. Outage probability is considered as the stationary distribution of the state transition matrix of the Markov chain [31]. The delay here is unbounded as it is not considered in the protocol formulation. An uplink general system involving multi-source multi-relays is analyzed in [36]. Adaptive link selection and rate transmission are studied. By optimizing the average sum-rate of the network, an adaptive link selection policy is derived. This policy uses the channel state information to its advantage. Since fairness is also an important issue in multi-source networks, an optimization to maximize throughput with max-min fairness constraints is considered. Following that, the link selection protocol is derived. By comparing the simulation results with conventional relaying schemes which have a priori-fixed transmission schedule, it is found that the proposed protocols achieve better average throughput [36]. However, delay, joint link selection or power allocation were not investigated.

# 2.3 Multiple Access Channels

Cover [37] was the first to study a broadcast channel where one source is transmitting to several destinations. Several different classes of channels are considered, e.g. binary symmetric channel, Gaussian channel, orthogonal channel and incompatible broadcast channels. By superimposing high-rate information on low-rate information, the upper bounds on the achievable rates are found to exceed those achieved by previous methods, i.e. time sharing and maxmin. The results are generalized for multiple senders to multiple receivers. Han [38] studied MAC where the sources have correlated information. Two cases are studied, namely, the case with a single MAC for a single receiver and with several MACs for several receivers. The capacity region for both cases are characterized based on the polymatroidal structure of conditional mutual information sets. Hui and Humblet [39] show that for the asynchronous MAC, it differs from the synchronous MAC by the lack of convex hull operation. This case has been studied for two users and then extended to a general case with more than two users. For the synchronous

case, the capacity region is defined by the convex hull of R.

Wyner [40] considered a cellular multiple access system. Shannon theoretic limits were obtained for a one dimensional linear array and a two dimensional hexagonal cellular system. Expressions for the largest achievable rate per transmitter were derived as the number of users grows large. As the interference increases, the maximum achievable rate increases or decreases depending on the signal-to-noise ratio. If it is less than unity, the maximum achievable rate will decrease and vice versa. Also, TDMA is found to give optimal performance inside the cell, but a suboptimal performance for adjacent cells. Yang et al. [41] considered the downlink multicell model with finite backhaul capacity. Upper bounds on the sum capacity for the network with two base stations and two users are studied and derived. The upper bound is shown to improve in the medium backhaul capacity range. It is also shown that the gap between lower and upper bounds on the sum capacity is narrowed down in the medium range. Kang et al. [42] studied the capacity of a diamond channel. The channel between the source and the two relays are considered to have finite different capacities and the link between the relays and the destination is considered as a MAC. Upper and lower bounds on the capacity of the diamond channel are proposed. The upper bound is derived from a single letterization of n-letter upper bound and is tighter than the cut-set bound. The lower bound is derived from an achievability scheme based on correlated codes through the MAC with superposition architecture. The two bounds are found to be similar. For the bounds to meet, sufficient and necessary conditions are provided which the Gaussian diamond MAC has to satisfy.

Padakandla and Pradhan [43] developed a coding method for communication over a general discrete MAC where channel state information are distributed at the transmitters. A new achievable rate region is derived by using the Abelian group codes and building an algebraic coding framework. Miridakis and Dimitrios [3] review the interference cancellation method and in particular SIC in communication networks. SIC has shown the best bit error rate (BER) performance of all interference cancellation methods. In particular, SIC added with orthogonal frequency division multiplexing (OFDM) approaches the Shannon capacity with single-antenna infrastructure. This capacity can even by extended while using multiple antennas. The SIC-OFDM methods is shown to be useful and applicable to a wide range of network implementations such as cellular, ad hoc and infrastructure based networks. Also, a performance complexity tradeoff factor is introduced to compare the various SIC-OFDM methods in the literature.

Zhang and Haenggi [4] studied the performance of SIC in fading wireless channels with power-law path loss. Using an analytical characterization of the performance of SIC as a function of the system parameters, the results show that the benefit of using SIC diminishes for a large dimensional network with small path loss exponent. However, when the users are clustered around the receiver, and very low-rate codes are used, SIC is found to be highly beneficial. For contemporary narrow-band systems e.g. LTE and Wifi, the gain of SIC is found to be mostly achieved by canceling a single interferer. Blomer and Jindal [5] compared two

interference cancellation methods, SIC and joint detection (JD) in wireless ad hoc networks. While SIC refers to successively decoding and subtracting signals, JD refers to simultaneous decoding of the desired signal and some of the strong interferers. Stochastic geometry is used to develop bounds on the outage probability. The bounds show that SIC and JD are comparable when the signal to interference ratio (SIR) threshold is less than one. However, when the SIR threshold becomes greater than one, JD shows a significant outage performance whereas SIC gives weak results.

## 2.4 Thesis Motivation

This section describes the motivation behind the work in this thesis. Based on the literature review of the seismic data acquisition system and the relaying network, we are motivated to study the seismic acquisition system from a theoretical perspective that we find lacking in the past works. The literature on the seismic acquisition system is mainly about practical implementations of the wireless technologies and techniques to provide services that enable the system to act autonomously. However, by studying the seismic acquisition system as a multi-user multi-relay system, we can observe from a higher layer how fundamental operations such as decoding order and selection could affect the whole efficiency of the system. By analyzing the seismic acquisition system from communication point of view, we can gain deep and fundamentally different insights into the system operation from what the practical implementations tell us. Thus, we decide to

study the sum-rate maximization of the communication system that a wireless seismic acquisition system represent. By using information theory tools, we can find the upper bounds on the achievable rates for each GP, and the upper bound on the total sum-rate. Furthermore, the transmission of data from the GWs to the DC is studied from different angles. First, by assuming small-size buffers at the GWs; we aim at finding the optimal power allocation for each GW and the optimal decoding order that the DC will use in order to minimize the total power expenditure. We also want to consider the case of large buffers, where the objective is to maximize a weighted sum of the GWs rates, given a total power constraint.

# CHAPTER 3

# SUM-RATE MAXIMIZATION OF THE GEOPHONES

In this chapter we consider the first stage of a seismic acquisition system. We develop a communication model for a seismic acquisition system in section one. The problem of maximizing the sum-rate of a group of GPs is considered in detail, and is mathematically formulated as an optimization problem in section two. In section three, five different metaheuristic algorithms are introduced and their parameters are explained. These algorithms are adapted and employed to solve the optimization problem and the results are presented in section four. Finally, the concluding remarks of the chapter are given in section five.

# 3.1 System Model

Consider the practical model of a seismic acquisition system given in Fig. 1.1. To study the information-theoretic sum-rate of the GPs, the system model has to

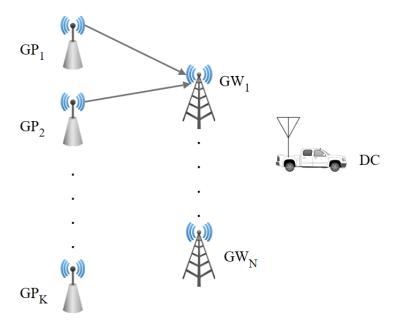


Figure 3.1: System model of the first stage of a seismic acquisition system

be designed in a way to separate the two stages of data delivery. Now, consider the system model shown in Fig. 3.1. The first stage will be the GPs-to-GWs stage, where each link between a GP and a GW will have some channel gain. GPs may send their sampled data to the GWs, where they are decoded and stored in buffers. The second stage will be the GWs-to-DC stage, where GWs will send their data that were previously received from the GPs. In this chapter, we focus on the first stage, which is the data delivery from the GPs-to-GWs.

We consider a system that consists of K GPs and N GWs. The channels between the GPs and the GWs follow Rayleigh block fading model. Channel gain, h, is assumed to be constant for a fixed interval of time but change independently after that. It is assumed to follow Rayleigh fading model, which is given by the following distribution,

$$f(h) = \frac{h}{\sigma^2} \exp(-\frac{h^2}{2\sigma^2}), \qquad h \ge 0, \tag{3.1}$$

where  $\sigma$  is a scale parameter of the distribution. We assume the transmission period to be a fixed time slot that is equal for all transmission sessions. We also assume information about the channels to be available at all the GWs. Each GP is assumed to transmit with a fixed power P. The channel matrix is H with  $K \times N$  dimension, so that each element of H represents a link between a GP and a GW.

The information sent over a communication link can be characterized by different parameters [44]. For example, the ergodic capacity describes the average rate of data sent over all time instants, where  $\bar{C} = E\left[\log_2\left(1 + \frac{P|h|^2}{N_0}\right)\right]$ . Here, the operation E[x] denotes the expectation of a random variable, x. The power of each GP is assumed to be constant. Therefore, the expectation operation is performed on the random channel gain. Ergodic capacity is usually used when the instantaneous CSI is not known at the transmitter. In this case, the transmitter will send with a constant rate over all fading states. Therefore, the effective capacity will be reduced. Another metric to measure the quality of the transmission over a channel is the outage probability. It is used when the receiver cannot successfully decoded the received symbols. The outage probability,  $P_{out} = Pr[\gamma < \gamma_{min}]$ , where  $\gamma$  denotes the received SNR and  $\gamma_{min}$  denotes the threshold SNR.  $\gamma_{min}$  is the minimum acceptable received SNR for the

signal to be decoded. In this scenario, the transmitter does not have the instantaneous CSI and sends with a constant rate. The rate of transmission is given by  $C_{out} = \log_2(1+\gamma_{min})$ , and it is successfully decoded with a probability  $1-P_{out}$ .

In this work, the instantaneous CSI is assumed to be known at the GPs.

Therefore, by sending with adaptive rate, the effective sent rate can be increased.

The Shannon normalized capacity for a Gaussian channel is given as,

$$C = \log_2\left(1 + \frac{P}{N_0}\right),\tag{3.2}$$

where the channel is characterized by the noise variance  $N_0$ . In a fading channel, Eq. 3.2 changes to the following formula,

$$C = \log_2 \left( 1 + \frac{P|h|^2}{N_0} \right), \tag{3.3}$$

where h is the channel gain value, taken from the channel matrix H. Each GP can send with a rate that is,  $R \leq C$ , which is called the achievable rate. We assume Gaussian codes that are capable of achieving C. For multiple GPs sending at the same time to a certain GW, a MAC is created, where the set of rates have to satisfy the capacity region. The capacity region for two GPs is given by the

following set of upper bounds:

$$R_{1} \leq \log_{2} \left( 1 + \frac{P_{1}|h_{1}|^{2}}{N_{0}} \right)$$

$$R_{2} \leq \log_{2} \left( 1 + \frac{P_{2}|h_{2}|^{2}}{N_{0}} \right)$$

$$R_{1} + R_{2} \leq \log_{2} \left( 1 + \frac{P_{1}|h_{1}|^{2} + P_{2}|h_{2}|^{2}}{N_{0}} \right)$$
(3.4)

SIC is known to achieve the maximum sum-rate at the capacity region by working at a corner of this region. By doing successive decoding, we can choose which corner to work at. If the GW decides to decode signal from  $GP_1$  first and then  $GP_2$ , the second inequality in Eq. 3.4 will hold for  $R_2$  and by subtracting the third inequality from the first inequality, we get the following bounds on the rates:

$$R_{1} \leq \log_{2} \left( 1 + \frac{P_{1}|h_{1}|^{2}}{N_{0} + P_{2}|h_{2}|^{2}} \right)$$

$$R_{2} \leq \log_{2} \left( 1 + \frac{P_{2}|h_{2}|^{2}}{N_{0}} \right)$$

$$R_{1} + R_{2} \leq \log_{2} \left( 1 + \frac{P_{1}|h_{1}|^{2} + P_{2}|h_{2}|^{2}}{N_{0}} \right)$$
(3.5)

We assume that each GW will select GP signals to be decoded at each time slot. Equipped with the channel information, the GWs will make an informed decision about the set of GPs to decode at each GW, with the aim of increasing the overall sum-rate. We assume the GWs can share information about their decoding sets and a central node will broadcast this information and do the processing needed to decide the best decoding selection settings. This central node can be one of

the GWs, or it can be the DC, where the decision is broadcast to all the GWs using backhaul links. GWs employ SIC, and they organize the set of GPs that they decide to decode in some order. In SIC, the GW will decode the first GP signal while considering all the other signals as interference. Then upon successful decoding, the GW subtracts this signal from the original signal. By repeating this process, the interference decreases successively until the last GP signal is decoded. The GP signal that is decoded last enjoys its maximum possible rate. We consider two scenarios for the seismic system depending on how frequent the GPs send their data:

#### 1. Scenario 1(Real-time):

The first scenario is a real-time scenario, where all the GPs will always transmit with a fixed power P at every time slot. In this case, we assume each GP to send its data as it finishes sampling. Therefore, there is no need for a buffer at the GP to hold the data. This case will always create interference in the system as all GPs are sending all of the time. In other words, it is better for all the GP signals to be decoded by one GW at least, as this will increase the sum-rate.

#### 2. Scenario 2 (Buffer-aided GPs):

In this scenario, the GPs are equipped with a buffer in which they can store their data. Thus, the GPs have the choice to send their data or not at a specific time slot. In this case, there is more freedom of choice, as some GPs can be off and others on depending on the channel state information. If a GP signal is not selected to be decoded by any GW, there is no need for it to be sending. Therefore, its power P=0 which reduces the interference present in the system. Overall, this can increase the sum-rate compared with Scenario 1 depending on the channel.

## 3.2 Problem Formulation

In this section, the optimization problem that is considered for the first stage is formulated and explained. The problem is formulated in a proper mathematical optimization form, where there is an objective function and a set of constraints. The optimization problem is done on a set of variables where the optimal values for these variables, that will maximize the objective function, are looked for. To formulate the problem mathematically some questions are expected to be answered.

- 1. Is it beneficial for all the GWs to decode all the GPs signals, or only some of them?
- 2. Which decoding order of the selected GPs to be adopted at each GW so as to maximize the sum-rate of all the GPs?

By choosing to decode all the GPs signals, additional constraints may hold on the rates, and therefore the rates could decrease unnecessarily. On the other hand, by choosing not to decode some of the GPs signals, the GW will have to consider them as interference. Thus, it is not clear right away whether a prior definite

decision should be made for all cases. Therefore, an optimization problem has to be formulated to choose the set of GPs to be decoded depending on the rates bounds.

To answer the second question, we find that it is more practical to let the GWs decode the signals of the selected GPs in a descending order. This will keep the sum-rate maximum by using SIC. Furthermore, fairness is added as the GP with minimum SNR will be decoded last, seeing no interference. Thus, it will enjoy its maximum possible rate. Therefore, in our work we will assume that the decoding order is done based on the SNR value, in a decreasing order.

To illustrate the effect of the decoding selection and the decoding order at the GWs let us consider two examples for a small network of K=3 GPs and N=2 GWs:

• Example 1: The channel gain matrix H is given as:

$$H = \begin{bmatrix} 3.023 & 1.133 \\ 1.738 & 2.168 \\ 0.542 & 0.896 \end{bmatrix}.$$

We set P=1W,  $N_0=1$ . In this case, by going through all possible decoding order combinations, the one that gives the maximum sum-rate is illustrated in Fig. 3.2, where  $GW_1$  decodes  $GP_2$  then  $GP_1$  while treating  $GP_3$  as interference and  $GW_2$  decodes  $GP_2$  then  $GP_3$  while treating  $GP_1$  as interference. In this case, the sum-rate is  $\sum R \leq 3.813$  bps/Hz. In this

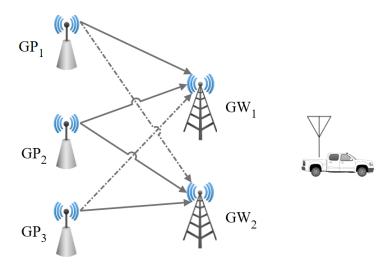


Figure 3.2: Example 1, all possible decoding order combinations are considered case, the set of upper bounds on the individual achievable rates are given by:

$$R_{1} \leq \log_{2} \left( 1 + \frac{P_{1}|h_{11}|^{2}}{N_{0} + P_{3}|h_{31}|^{2}} \right)$$

$$R_{2} \leq \min \left( \log_{2} \left( 1 + \frac{P_{2}|h_{21}|^{2}}{N_{0} + P_{1}|h_{11}|^{2} + P_{3}|h_{31}^{2}|} \right),$$

$$\log_{2} \left( 1 + \frac{P_{2}|h_{22}|^{2}}{N_{0} + P_{1}|h_{12}|^{2} + P_{3}|h_{32}^{2}|} \right) \right)$$

$$R_{3} \leq \log_{2} \left( 1 + \frac{P_{3}|h_{32}|^{2}}{N_{0} + P_{1}|h_{12}|^{2}} \right)$$

$$(3.6)$$

When each GW is forced to decode following the descending order, we notice that there will be fewer options. In this case, the sum-rate is decreased slightly, to be  $\sum R \leq 3.749$  bps/Hz. The best decoding selection and order for the GWs is, GW<sub>1</sub> decodes GP<sub>1</sub> then GP<sub>2</sub> then GP<sub>3</sub> and GW<sub>2</sub> will not decode any signal, as illustrated in Fig. 3.3. The set of upper bounds on

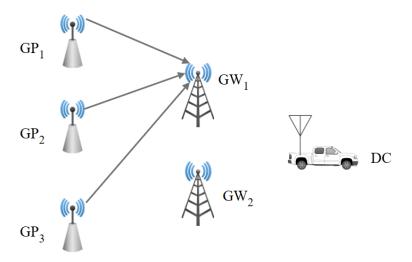


Figure 3.3: Example 1, best decoding order by following decreasing order at the GWs

the individual achievable rates are given by:

$$R_{1} \leq \log_{2} \left( 1 + \frac{P_{1}|h_{11}|^{2}}{N_{0} + P_{2}|h_{21}|^{2} + P_{3}|h_{31}|^{2}} \right)$$

$$R_{2} \leq \log_{2} \left( 1 + \frac{P_{2}|h_{21}|^{2}}{N_{0} + P_{3}|h_{31}|^{2}} \right)$$

$$R_{3} \leq \log_{2} \left( 1 + \frac{P_{3}|h_{31}|^{2}}{N_{0}} \right)$$
(3.7)

Now let us compare these two cases with the case when all the GWs will perform decoding for all the GPs without doing any kind of optimization. In this case we find that  $\sum R \leq 2.483$  bps/Hz. The reason is that sometimes decoding a GP at all the GWs puts more constraints on the rate of that GP, which might result in reducing that rate.

• Example 2: The channel gain matrix H is given as,

$$H = \left[ \begin{array}{cc} 0.8 & 0.2 \\ 0.3 & 0.7 \\ 0.1 & 0.5 \end{array} \right].$$

We set P=1W,  $N_0=1$ . By going through decoding order combinations in decreasing order, the one that gives the maximum sum-rate is illustrated in Fig. 3.4, where  $GW_1$  decodes  $GP_1$  while treating  $GP_2$  and  $GP_3$  as interference and  $GW_2$  decodes  $GP_2$  then  $GP_3$  while treating  $GP_1$  as interference. In this case, the sum-rate is  $\sum R \leq 1.436$  bps/Hz. In this case, the set of upper bounds on the individual achievable rates are given by:

$$R_{1} \leq \log_{2} \left( 1 + \frac{P_{1}|h_{11}|^{2}}{N_{0} + P_{2}|h_{21}|^{2} + P_{3}|h_{31}|^{2}} \right)$$

$$R_{2} \leq \log_{2} \left( 1 + \frac{P_{2}|h_{22}|^{2}}{N_{0} + P_{1}|h_{12}|^{2} + P_{3}|h_{32}^{2}|} \right)$$

$$R_{3} \leq \log_{2} \left( 1 + \frac{P_{3}|h_{32}|^{2}}{N_{0} + P_{1}|h_{12}|^{2}} \right)$$
(3.8)

Now let us compare this with the case when all the GWs will perform decoding for all the GPs without doing any kind of optimization. In this case we find that  $\sum R \le 0.194$  bps/Hz.

Therefore, for some GPs, it might be better not to decode them at all GWs, and this is the optimization problem that we consider in this paper; how to optimize the set of GPs to be decoded at each GW so as to maximize the

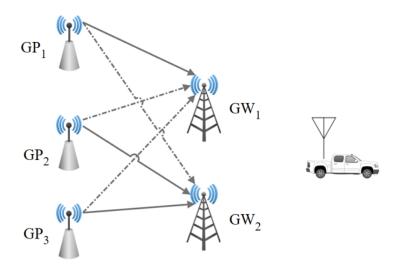


Figure 3.4: Example 2, the best decoding order.

network sum-rate.

Since the GP selection and the decoding order at the GWs will play an important role in maximizing the sum-rate, the problem can be formulated as a discrete problem with discrete variables. The variables that are considered for the optimization problem are the links indices. By choosing a value of zero or one for the indices, the GWs will decide if they will decode this GP signal or not. By choosing one for the link index, the GW will decode the GP signal. On the other hand, by choosing zero for the link index, the GW will consider the signal of the GP as interference, i.e. not decoding it. The sum-rate maximization problem is

formulated as an integer constrained optimization problem as follows:

$$\max_{F_{ji}} \sum_{j=1}^{K} R_{j}, \quad \text{subject to}$$

$$\sum_{j \in Q} F_{ji} R_{j} \leq \log_{2} \left( 1 + \frac{\sum_{j \in Q} F_{ji} P_{j} |h_{ji}|^{2}}{N_{0} + \sum_{\substack{m=1 \ m \neq j}}^{K} (1 - F_{mi} P_{m} |h_{mi}|^{2})} \right),$$

$$F_{ji} \in 0, 1, \forall j \in \{1, 2, ..., K\}, i \in \{1, 2, ..., N\}, \tag{3.9}$$

where R is the actual rate of the GP and Q is the group of all combinations  $\binom{K}{b}$ ,  $\forall b \in \{1, 2, K\}$ . Here every link will have an index  $F_{ji}$  that is one if the  $i^{th}$  GW decides to decode the signal of the  $j^{th}$  GP, otherwise as zero. The set of constraints is a generalized form of the multiple access channel constraints (with multiple destinations), and it gives all the combinations of upper bounds on the achievable rates for all GWs. Each GW will decode the GP signals in a decreasing order, starting from the signal with highest SNR down to the signal with the minimum SNR. This will feature fairness to the weaker signals, while providing the maximum sum-rate. The optimization therefore is performed on the links indices;  $F_{ji}$ . This makes the problem an integer programming problem where we have many options to explore.

The search space described by this problem is comprised of all possible decoding order combinations. Its size is given by the following formula:

$$\zeta = \left[\sum_{i=0}^{K} {K \choose i} \right]^{N}, \tag{3.10}$$

To give an idea about how rapidly the size of this search space increases, consider a small network where K=3 GPs and N=2 GWs, then from Eq. 2.5, we find that =64 combinations while when we increase the parameters to be K=30 and N=5, we find  $\zeta=1.427\times10^{45}$  combinations. Going through all the combinations is of course an impossible task and consumes unrealistic resources of time and computational effort. We therefore look for heuristic and metaheuristic methods to solve this problem. In the next section, we introduce three sets of metaheuristic algorithms to solve the problem in Eq. 3.8. Specifically, we discuss two variations of particle swarm optimization (PSO), two variations of ant colony optimization (ACO) and the simulated annealing (SA) method.

# 3.3 Proposed Algorithms

In this section, we introduce the proposed algorithms, their philosophy and the mathematical formulas they entail.

# 3.3.1 Particle Swarm Optimization

PSO is based on the study and simulation of social behavior of bird flocks and fish school. The emulation of the social mechanisms of nature have been rewarding in their applications in computer engineering, especially to solve difficult problems. Scientists began from earlier times to study how living species interact with each other and how they approach their daily lives problems e.g. searching for food. What looks to be a stochastic phenomena turns to have a set of underlying

paradigms that can be applicable for complicated problems with great efficiency. PSO is one example of an application that is both simple to implement and very effective across wide range of problems [45, 46, 47, 48, 49, 50, 51, 52, 53]. For an introduction to PSO, see [54].

PSO uses simple velocity and position equations to update the particles positions which correspond to the proposed solution. All the particles search for the global optimal solution. The particles compute, use and mutually share information about the best achieved solutions so far. Some variations were proposed in the literature to solve discrete/binary optimization problems. We propose two variations of PSO to approach the problem in Eq. 3.8, namely, angle-modulated particle swarm optimization (AMPSO) and discrete particle swarm optimization (DPSO).

#### Angle-modulated Particle Swarm Optimization

This algorithm uses continuous PSO to optimize four variables instead of the whole binary vector [55, 50, 56, 57]. This has proved efficiency, especially when the dimensionality of the binary vector is large. A function composed of sine and cosine in given in Eq. 3.11 which is derived from angle-modulation theory is optimized using PSO. This function is used because of its ability to represent large vector of bits by carefully tuning its parameters,

$$H(x) = \sin(2\pi(x-a)b\cos(A)) + d,$$
 (3.11)

where,  $A = 2\pi c(x - a)$ , a is the horizontal shift, b is the maximum frequency of the sine function, c is the maximum frequency of the cosine (also affects the rate at which the frequency of the sine signal changes), d is the vertical shift and x is a single element from a set of evenly separated intervals based on the number of bits. The parameters of Eq. 3.11 are fed into the velocity equation to update their values and obtain the positions of the new parameters. The velocity equation is given below:

$$V_n(t+1) = \Phi V_n(t) + C_1 R_1 \times (L_n(t) - S_n(t) + C_2 R_2 \times (G(t) - S_n(t))), \quad (3.12)$$

where  $\Phi$  is the inertia factor,  $L_n(t)$  is the local best value, G(t) is the global best value,  $S_n(t)$  is the current optimized variable.  $C_1$  and  $C_2$  are the weights given to the local best and global best values, respectively.  $R_1$  and  $R_2$  refer to random numbers that are drawn from a uniform distribution between zero and one, U(0,1). A flowchart detailing the steps of the AMPSO algorithm is shown in Fig. 3.5.

#### Discrete Particle Swarm Optimization

Here the position for a variable can be either zero or one. This raises the need to change the way of thinking about velocity. Velocity here is the probability that a bit is one, where y represents the index of the particle and z represents the index of the dimension [58]. The dimensionality of the vector of bits is  $D = N \times K$ .

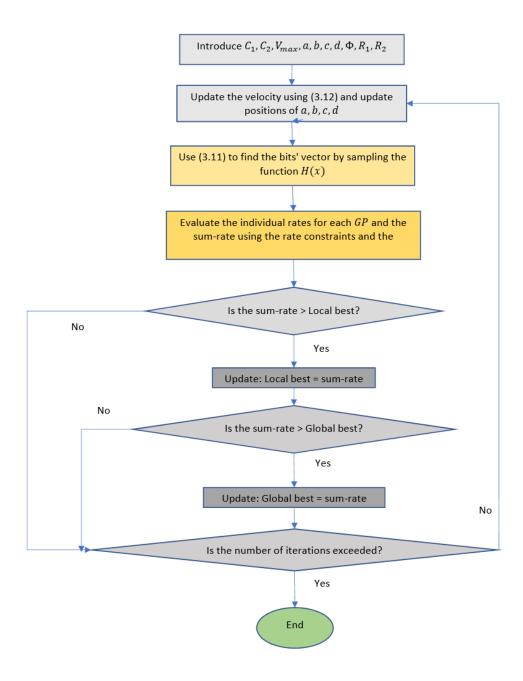


Figure 3.5: A flowchart of the AMPSO algorithm showing detailed steps

The velocity formula is given as:

$$V_{yz} = V_{yz} + \phi(p_{yz} - x_{yz} + \phi(p_{gz} - x_{yz})), \tag{3.13}$$

where xyz is the position of the  $y^{th}$  particle in the  $d^{th}$  dimension.  $p_{yz}$  is the bit position of the best performance the  $y^{th}$  particle has achieved so far.  $p_{gz}$  is the bit position for the best performance of all the particles so far (global solution). Obviously,  $V_{yz}$  here is a real-valued number and hence we want to transform it to a probability. In order to do that, a logistical transformation called Sigmoid function is used. It is given as:

$$S(V_{yz}) = \frac{1}{1 + \exp(-V_{yz})},\tag{3.14}$$

To determine  $x_{yz}$ , a random value  $\rho$  is generated from a uniform distribution in the range [0,1]. Then it goes through the following decision rule:

if 
$$\rho < S(V_{yz})$$
,  $x_{yz} = 1$ ,  
else  $x_{yz} = 0$ . (3.15)

If the velocity is not bounded, the algorithm might stop exploring new regions in the search space. This in turn can cause the algorithm to get stuck in a local optimum. To avoid that, a bound is usually set so that the algorithm keeps exploring the search space. A flowchart that illustrate the DPSO steps is shown

## 3.3.2 Ant Colony Optimization

(ACO) is a probabilistic metaheuristic that is based on observations of the behavior of real ants[59, 60, 61, 62, 63]. Ants are blind, and they live in communities. They search randomly for food. When going from the nest to food source, they want to remember the path and guide other ants towards it. So, in their path towards home they release some chemical substance called pheromone which can be tracked by other ants. Pheromone evaporates with time. If there is more than one path that is taken by the ants, the shorter path will hold pheromone longer since ants take less time walking through it. Thus, eventually all the ants will use this shorter path.

Based on this, many algorithms were developed which use artificial ants and artificial pheromone. Pheromone represents remembering the promising parts of the search space. Pheromone evaporation allows the ants to explore other parts of the search space and avoid being trapped in a local optimum. The algorithm of the ACO consists of the following main steps:

- Set parameters and initialize pheromone
- While termination condition is not met
  - Construct solutions
  - Apply local search (optional)

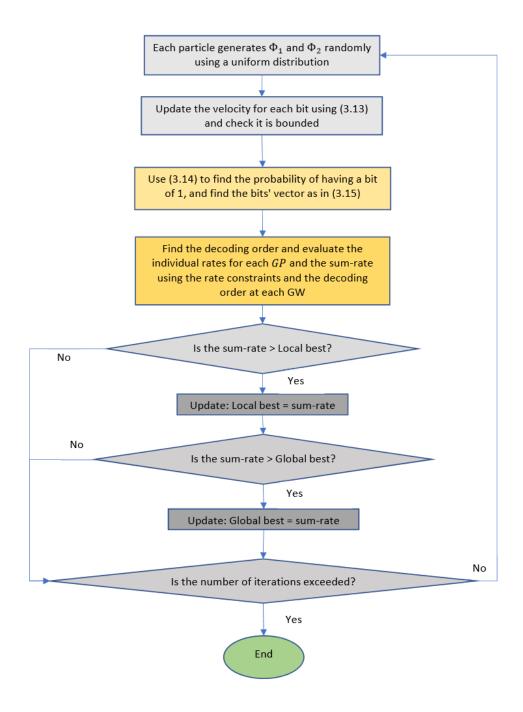


Figure 3.6: A flowchart showing detailed steps of the DPSO algorithm

#### - Update Pheromones

#### • End

Two varieties of ACO algorithms have been developed in the literature, namely, ant system (AS) and max-min ant system (MMAS).

### Ant System

All ants that successfully constructed a solution update the pheromone values at each iteration.

$$\tau_{cd}^{new} = (1 - \gamma)\tau_{cd}^{old} + \sum_{r=1}^{m} \Delta \tau_{cd}^{r},$$
(3.16)

where  $\gamma$  is the evaporation coefficient, m is number of ants,  $c \in \{0,1\}$  is the index of possible outcomes,  $d \in \{1,2,...,D\}$  where D is the dimensionality of the system and  $D = K \times N$ . When constructing a solution, the probability of Ant q choosing  $c \in \{0,1\}$  for the  $d^{th}$  bit is given by:

$$p_{cd}^{q} = \frac{\tau_{cd}^{\alpha} \eta_{cd}^{\beta}}{\sum_{c \in N(s^{P})} \tau_{cd}^{\alpha} \eta_{cd}^{\beta}},$$
(3.17)

where  $N(s^P)$  is the set of feasible components, i.e.  $\{0,1\}$  and  $\eta_{cd}$  is the heuristic information, which depends on the problem at hand.  $\alpha$  and  $\beta$  represent the weight given to the pheromone and to the heuristic information, respectively.

#### Max-Min Ant System

Here only the best ant updates the pheromone values. Also, the pheromone update is bounded as follows:

$$\tau_{cd}^{new} = [(1 - \rho)\tau_{cd}^{old} + \Delta \tau_{cd}^r]_{\tau_{min}}^{\tau_{max}}, \tag{3.18}$$

where  $\tau_{max}$  is the maximum possible value of the pheromone and  $\tau_{min}$  is the minimum possible value of pheromone. A flowchart that shows the steps of AS and MMAS algorithms is shown in Fig. 3.7

## 3.3.3 Simulated Annealing

(SA) is a metaheuristic method based on the metal annealing in material science [64]. It uses restarts to avoid being trapped in a local maximum. It always accepts moves that improve the value of the objective function. If the move does not improve the objective function, then the algorithm may accept the move with some probability. This probability assumes its highest value at the beginning of the algorithm. So, the algorithm is more willing to accept moves that do not improve the objective function at the beginning to explore the search space. As the number of iterations increases, that probability decreases by cooling the temperature gradually. Hence the algorithm is less willing to trade a worse position by its current position.

We propose a low-complexity version of SA for binary problems, where the solution will be a vector of bits corresponding to the links indices vector;  $F_{ji}$ . The

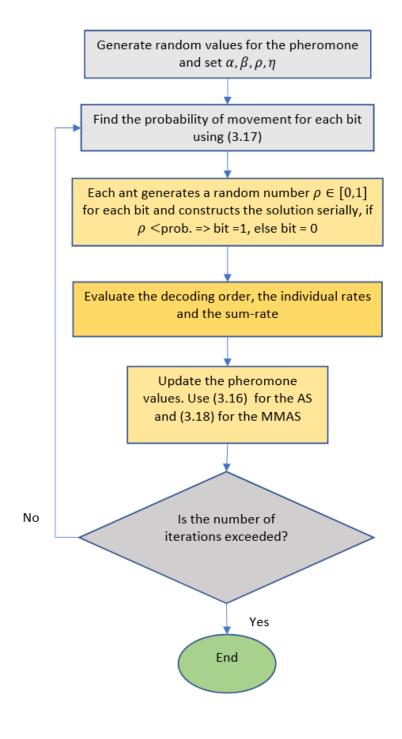


Figure 3.7: A flowchart showing detailed steps of the ACO algorithm

developed algorithm is shown in steps in Fig. 3.8, where T is the temperature value,  $\Delta E$  is the difference in sum-rate between the best solution so far and the next solution and f is a factor that controls the exploration capability.

The solution generated from the neighbourhood by randomly flipping a number of vector bits. The position of the chosen vector bits is chosen randomly from the set [1, ..., D], where  $D = K \times N$ . We note that in order for the algorithm to converge,  $T_{max}$  should be large enough. This depends on the given problem and its search space size. For satisfying results, we advise that  $T_{max}$  should be at least 0.1% of the number decoding order combinations. This is because the algorithm needs to explore the search space to a certain degree before converging. Giving lower value for  $T_{max}$  may result in slow convergence and bad results.

# 3.4 Results

In this section, the simulation parameters for the proposed algorithms are presented. The results for a number of examples illustrating different values for K and N are shown. It is observed that as the values of K and N gets large and the search space gets too large some of the algorithms proposed get stagnant. By using a limited computational budget, the convergence speed of the algorithms could get slow, which affect the efficiency of the results. This problem is solved for the ACO algorithms by using a different approach for setting the heuristic information parameter.

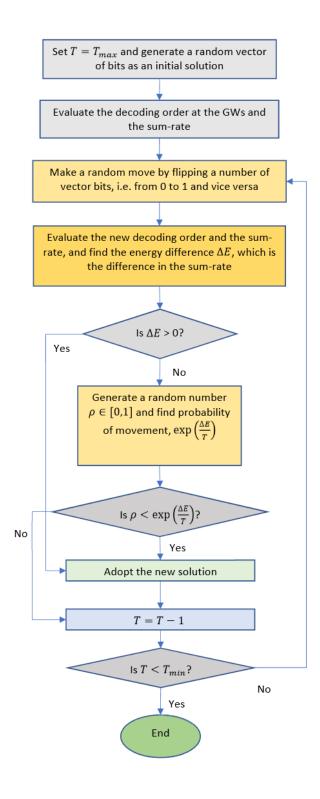


Figure 3.8: A flowchart illustrating detailed steps of the SA algorithm

#### 3.4.1 Simulation Parameters

In our simulations, we give a limited computational budget to the proposed algorithms. The complexity is represented as the maximum temperature (T) for SA, number of particles/ants (M) and iterations (I) for MMAS/AS/DPSO/AMPSO. For AMPSO, we choose  $C_1$  and  $C_2$  to be 1.49618,  $\Phi$  is set to 0.729844 and  $V_{max}$  is set to 4 [65]. For DPSO,  $V_{max}$  is set to 6. In AS,  $\alpha=1$ ,  $\beta=1$ ,  $\eta_{cd}$  equals the channel gain when c=1 and equals the average of the other channel gains for the same GW when c=0. In MMAS,  $\tau_{max}=-\tau_{min}=7$ . In SA,  $f=100\times T_{max}$ . We arrived at these values by following the references and by experimenting with simulation.

We differentiate between the results for small networks and large networks. When K and N are small, we can find the optimal solution by trying each possible decoding order combination. The exhaustive search (ES) is an algorithm which generates all possible decoding order combinations and finds the corresponding sum-rate. It keeps the decoding order that gives the maximum sum-rate by comparing the best solution so far with the next solution. We compare the performance of the proposed algorithms with the ES. When the search space gets too large, however, the ES cannot be used because the time it would take is impractical. Therefore, we use the case where the GWs decode all the GPs as a baseline. This no-optimization case is when the GWs do not optimize the set of decoding order and they simply decode all the signals starting with the GP with maximum channel and going in a descending order.

### 3.4.2 Results for small networks

Several networks are studied by generating different channels using Rayleigh fading model, with  $\sigma=1$ . We set P=1W and the noise variance,  $N_0=1$ . In the following, we show the corresponding channel for each example. All the rates are in bits per second per Hz bps/Hz. All the algorithms results are averaged over 10 trials.

#### • Example 1:

A network of K=8 GPs and N=2 GWs is considered. The complexity of ES is 65,536 decoding order combinations. The channel gain matrix is given by,

$$H = \begin{bmatrix} 0.80 & 2.02 \\ 1.55 & 1.43 \\ 0.89 & 1.07 \\ 1.06 & 1.57 \\ 1.93 & 1.61 \\ 1.84 & 0.65 \\ 0.95 & 1.01 \\ 0.46 & 1.82 \end{bmatrix}.$$

The results for the ES and proposed algorithms for three different levels of complexity are shown in Table 3.1.

Table 3.1: Example 1

ES	AS	DPSO	SA	AMPSO	Complexity
4.3251	4.3225	4.177	4.2573	4.0714	T=6000
4.0201	4.0220	4.2373 4.0714		M=10, I=600	
4.3251	4.1964	4.1675	3.9846	4.0959	T=600
1.0201	1.1501	1.1079	0.0010	1.0000	M=10, I=60
4.3251	3.8982	3.8173	3.6323	3.57	T=60
4.0201	0.0302	0.0170	0.0020	0.01	M=1, I=60

#### • Example 2:

A network of K=5 GPs and N=3 GWs is considered. The complexity of ES is 32,768 decoding order combinations. The channel gain matrix is given by,

$$H = \begin{bmatrix} 2.94 & 1.26 & 0.89 \\ 1.09 & 3.15 & 1.17 \\ 0.36 & 1.11 & 1.22 \\ 0.77 & 3.51 & 0.49 \\ 1.01 & 1.73 & 1.44 \end{bmatrix}.$$

The results for the ES and proposed algorithms for three different levels of complexity are shown in Table 3.2.

Table 3.2: Example 2

ES	MMAS	DPSO	SA	AMPSO	Complexity
					T=6000
5.4514	5.4514	5.2882	5.3488	5.2878	M=10, I=600
					T=600
5.4514	5.3026	4.9219	4.9474	4.7468	M=10,
					I=60
5.4514	4.8975	3.7356	4.0963	3.7421	T=60
					M=1, I=60

#### • Example 3:

A network of K=4 GPs and N=4 GWs is considered. The complexity of ES is 65,536 decoding order combinations. The channel gain matrix is given by,

$$H = \begin{bmatrix} 1.01 & 0.58 & 0.65 & 0.90 \\ 2.66 & 1.08 & 2.03 & 0.45 \\ \\ 0.62 & 1.53 & 1.45 & 1.15 \\ \\ 1.25 & 0.99 & 2.08 & 1.02 \end{bmatrix}.$$

The results for the ES and proposed algorithms for three different levels of complexity are shown in Table 3.3.

Table 3.3: Example 3

ES	MMAS	DPSO	SA	AMPSO	Complexity
3.8732	3.793	3.7367	3.711	3.5871	T=6000
					M=10, I=600
3.8732	3.5332	3.5766	3.466	3.6335	T=600
					M=10, I=60
3.8732	3.3554	3.1243	3.0757	2.7133	T=60
					M=1, I=60

# • Example 4:

A network of K=10 GPs and N=2 GWs is considered. The complexity of ES

is 1,048,576 decoding order combinations. The channel gain matrix is given by,

$$H = \begin{bmatrix} 1.73 & 1.06 \\ 1.16 & 1.09 \\ 0.06 & 1.84 \\ 1.07 & 1.39 \\ 1.66 & 0.43 \\ 0.35 & 1.11 \\ 2.72 & 1.32 \\ 1.99 & 1.32 \\ 0.78 & 0.67 \\ 1.49 & 1.08 \end{bmatrix}$$

The results for the ES and proposed algorithms for three different levels of complexity are shown in Table 3.4.

Table 3.4: Example 4

ES	MMAS	DPSO	SA	AMPSO	Complexity
4.9519	4.9336	4.7291	4.7741	4.7224	T=6000
4.5515	4.9550	4.7291	4.7741	4.1224	M=10, I=600
4.9519	4.8909	4.5819	4.6083	4.4225	T=600
					M=10, I=60
4.9519	4.5509	4.1638	3.9245	4.1689	T=60
4.5015	1.0000	4.1000	0.0240	4.1003	M=1, I=60

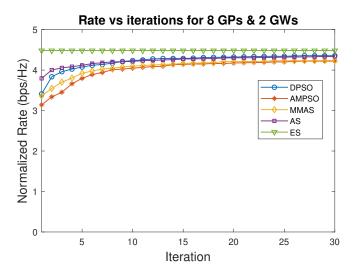


Figure 3.9: Normalized rate vs. iterations for K = 8 GPs and N = 2 GWs

From the previous examples it is noticed that all the algorithms achieve comparable results with the ES when the complexity is higher. As the computational complexity represented by T, M and I gets lower, a noticeable decrease in the performance is recorded.

Next, the normalized rate is plotted vs. the iterations for K=8 GPs and N=2 GWs. The performance of the algorithms is compared with the optimal solution, obtained via the ES. The size of the search space that the ES looks through is  $\zeta=65,536$  combinations. For the algorithms here, we give a fixed computational budget of: M=30 and I=30. Furthermore, the results are averaged over 50 random channel realizations. As can be seen in Fig. 3.9, the AS and DPSO achieve better results, while MMAS and AMPSO achieve slightly worse results. However, all converge into values close to the optimal solution.

Furthermore, the minimum square error for the algorithms (MSE) is computed with respect to the ES. The error is defined as the difference between the optimal

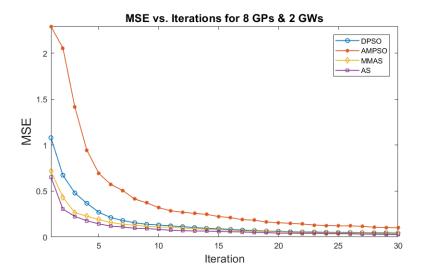


Figure 3.10: MSE vs. Iterations for K = 8 GPs and N = 2 GWs

solution and the algorithm's proposed solution. Fig. 3.10 shows the MSE vs. iterations for K=8 GPs and N=2 GWs. A fixed computational budget is given to the algorithms which consist of: M=30 and I=30. Furthermore, the results are averaged over 100 random channel realizations. As can be seen in Fig. 3.10, AS achieves the best convergence results. Secondly, MMAS achieve comparable results. DPSO is the third in convergence speed. All the algorithms mentioned above converge into the same MSE value. AMPSO, however, has the slowest convergence and scores the worst results for the final MSE value.

# 3.4.3 Results for Large Networks

To describe realistic surveys, number of GPs and GWs must be larger. Therefore, here we consider an example of K=100 and N=8. The number of decoding order combinations here is beyond the capabilities of any practical computer;  $\zeta=6.67\times 10^{240}$  combinations. Therefore, the use of the proposed algorithms

with a limited complexity becomes very crucial in such cases. We consider two different scenarios for how the GPs transmit data to the GWs.

# 3.4.4 Scenario 1) (Real-time)

In this scenario the powers of all GPs are fixed. Here it is more beneficial to decode all the signals sent by the GPs due to the existence of interference all the time, whether the GP signal is decoded or not. Fig. 3.11 shows the normalized rate in (bps/Hz) vs. iterations. The results are averaged over 50 random channel realizations. The channels follow Rayleigh fading with  $N_0 = 1$ . Here the used parameters are: M = 250 and I = 40. As can be seen, AS achieves the best result followed by MMAS, DPSO and finally AMPSO. Table 3.6 shows an example

Table 3.5: Algorithms performance for K=8 and N=2

ES	MMAS	AS	DPSO	SA	AMPSO	Complexity
5.49	5.34	5.41	5.49	5.32	5.31	T = 6000 $M = 10$ , $I = 600$
5.49	5.11	5.17	5.21	4.77	4.76	T = 600 $M = 10$ , $I = 60$
5.49	4.34	4.68	4.32	3.94	4.03	T=60 $M=1,$ $I=60$

comparing the performance of no-optimization and the proposed algorithms in Scenario 1 for a large network of 100 GPs and 8 GWs. The no-optimization case is the special case where the GWs neither cooperate nor share information about the decoding order. In this case we assume all the GWs will decode all the signals coming from the GPs. The order will be descending, starting from signal with

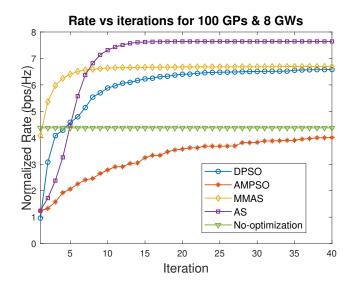


Figure 3.11: Normalized rate vs. Iterations for K = 100 and N = 8. Scenario 1 maximum channel gain to the signal with minimum channel gain.

# 3.4.5 Scenario 2) (Buffer-Aided GPs)

We assume all the GPs have buffers where they can store the sampled data before transmission. In this scenario the decoding order of the GWs can be optimized so that the sum-rate is even improved over Scenario 1. This is achieved through deactivation of some of the GPs that generally have low channel quality. Fig. 3.12 shows the normalized rate in (bps/Hz) vs. iterations and the results are averaged over 50 random channel realizations. Here the used parameters are: M=250 and I=40. We find that the best result is achieved by AS, closely followed by MMAS and DPSO and finally AMPSO. Table 3.7 shows an example comparing the performance of no-optimization and the proposed algorithms in Scenario 2 for a network of 100 GPs and 8 GWs. Tables 3.6 and 3.7 are for the same channel

gain matrix. Compared to the small network of K = 8 and N = 2, we see that SA achieves a lower sum-rate value compared to the no-optimization case. Also,

Table 3.6: (Scenario 1) Algorithms performance for K = 100 and N = 8

Algorithms and no-optimization	Sum-rate (bps/Hz)
No optimization	4.33
DPSO	6.32
AMPSO	4.33
SA	2.16
AS	7.77
AS ( not problem-specific)	4.66
MMAS	6.92
MMAS ( not problem-specific)	1.87

we notice that AS and MMAS achieve lower sum-rate values when their heuristic information is not adapted. This is an interesting observation which indicates the effect of the convergence speed of metaheuristic algorithms on their capability to explore the search space in a limited time. Although AS and MMAS belong to ACO algorithms, which was proved to always converge, the convergence speed is a problem that is still not fully explored [62, 63]. To overcome the issue of the algorithms stagnation, we study the effects of various parameters such as  $\gamma, \alpha, \beta$  and  $\eta$ . Except for  $\eta$ , we found through simulation that the effects of all parameters on convergence speed are minimal. However, for  $\eta$ , the choice of the heuristic information will greatly influence the results. This is because  $\eta$  biases the search towards regions that are expected to be promising. For Scenario 1, we give a weight to each GW that is proportional to the average of the channels gains associated between all the GPs and this GW. The higher the average for a certain GW, it is more likely to decode signals from GPs. This helps increase the sumrate because when a GW decodes a number of GPs signals, it will successively

eliminate the interference as it is decoding, which increases the total sum-rate overall. For Scenario 2, it would be useful to turn off GPs which have all their links as weak channels. The reason is that those GPs have very small rate, and they will cause interference for other users. Therefore, removing them will reduce the unnecessarily limiting interference present in the network, which will help increase the rate of other GPs, while only losing the small rate that belongs to those GPs. To do this we increase the probability of having an index of 0 for the links associated with these GPs. This makes it more probable that GWs will not decode GPs that have low channel gains. We combine this with the Scenario 1 measure, where each GW will have a weight to its links that is proportional to the channel gains average. The combined effect directs the search towards regions that have higher sum-rate and thus increases the algorithm performance with limited budget. Table 3.8 shows the time taken by each algorithm to search for optimal solution for the same scenario considered in Table 3.6.

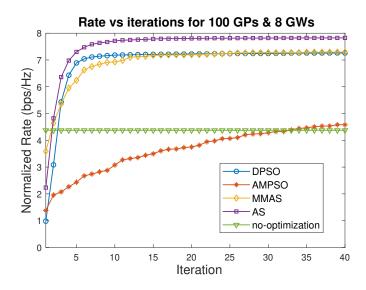


Figure 3.12: Normalized rate vs. Iterations for K=100 and N=8. Scenario 2

Table 3.7: (Scenario 2) Algorithms Performance for K=100 and N=8

Algorithms and no-optimization	Sum-rate $(bps/Hz)$
No optimization	4.33
DPSO	7.51
AMPSO	3.36
SA	2.24
AS	7.87
AS ( not problem-specific)	3.62
MMAS	7.17
MMAS ( not problem-specific)	2.93

Table 3.8: Time taken by proposed algorithms to search for optimal solution

Algorithm	Time in seconds
DPSO	40
AMPSO	69.9531
SA	6.67
AS	13.156
MMAS	14.5

# 3.5 Concluding Remarks

In this chapter, we considered the first stage in a wireless seismic acquisition system, where GPs send their sampled data to a few GWs. The goal is the maximization of sum-rate using information theoretic bounds. Several metaheuristic algorithms are proposed based on concepts from swarm intelligence and material science. Results for small and large networks are shown. For small networks, algorithms achieve comparable results with ES. However, when the search space gets very large, convergence speed for SA and ACO algorithms get stagnant. The speed of convergence for the ACO algorithms can be increased by adapting the heuristic information accordingly so that the algorithms are biased towards promising regions earlier.

# CHAPTER 4

# DATA DELIVERY FROM GATEWAYS TO DATA

# **CENTER**

In this chapter, the second stage in the seismic acquisition system is considered. The received signals from the GPs have been received by the GWs, successfully decoded and stored in each buffer. The occupancy of each buffer depends on the rate of data sent by the GPs. We consider two cases based on the size of the buffer of the GW. First, small and limited buffers are assumed. These buffers can receive only one set of data from the GPs. Two different optimization problems are proposed. The convexity of each problem is studied and proved. After that simulation results are presented. Furthermore, the case of large buffers is considered at the GWs. These buffers can hold large amount of data for sometime and it is not necessary to send all the data to the DC in one transmission session. A

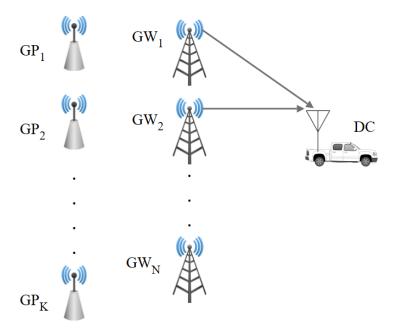


Figure 4.1: System model of the second stage of a seismic acquisition system problem of power allocation and study of decoding order at the DC is formulated. Convexity of the problem is studied and proved. Results based on simulation are presented. Finally, the chapter is concluded with final remarks.

# 4.1 System Model

A system of K GPs, N GWs and a DC is considered. The system model is shown in Fig. 4.1. The channels between each GW and the DC follow Rayleigh block fading model given in Eq. 2.1. We assume the transmission period to be a fixed time slot that is equal for all transmission sessions. The information about the channels are assumed to be available at the GWs. The channel matrix G is of  $1 \times N$  dimension. Each element of G represents a channel link between a GW and the DC. The normalized capacity capacity for a fading channel is represented by:

$$C = \log_2\left(1 + \frac{P|g_i|^2}{N_0}\right),\tag{4.1}$$

where  $g_i$  is the channel gain value between the  $i^{th}$  GW and the DC. For multiple GWs sending at the same time to the DC, a MAC is created, where the set of GWs rates are limited by the boundaries of the capacity region. SIC is considered at the DC, since it is known to achieve the maximum sum-rate of the capacity region by working at one of its corners. We assume variable power transmission in this chapter, where power allocation is utilized achieve the objective of each problem that is considered in this chapter.

# 4.2 Gateways Equipped with Small Buffers

First, small-size buffers are assumed at the GWs. In this case, each GW has data stored in its buffer. This data was received in the previous transmission periods. The objective is to send all this data to the DC. Thus, the GW will extract the stored data from the buffer, encode it using codes that are capable of achieving Gaussian capacity and send it over the channel to the DC. In this case, the GW should send all the data so that it can be ready for receiving data from the GPs in the future. Any data that is not sent in this stage will be discarded as the GW prepares to receive new set of data from the GPs. In this section, two problems are formulated with different objective functions. The convexity of each problem is studied and proved. A proposition for the first problem is shown and its proof is also presented. Finally, the simulation results are presented for both problems.

#### 4.2.1 Problem 1 Formulation

The first problem considers the case of data delivery from the GWs to the DC with minimal total power. The problem is formulated as an optimization problem, where the variables of optimization are the individual transmission powers of the GWs, and the decoding order at the DC. The importance of the decoding order is that it affects the individual rate for each GW. All the data at the GWs have to be transmitted. So, the set of all possible combinations of upper bounds on the rates form constraints on the normalized data. For practical consideration, each GW can send with power that is less than a maximum value,  $P_{max}$ . The problem is shown below,

$$\begin{aligned} & \min_{P_i, \forall i} & P_{\text{Total}} & \text{subject to} \\ & \text{Decoding order} \\ & 0 \leq P_i \leq P_{max} \\ & \sum_{i \in W} Q_i \leq \log_2 \Big(1 + \frac{\sum_{i \in W} P_i |g_i|^2}{N_0} \Big), \end{aligned} \tag{4.2}$$

where  $P_{\text{Total}} = \sum_{i=1}^{N} P_i$ , W is the group of all possible combinations  $\binom{N}{b}$ ,  $\forall b \in 1, ..., N$ . Here,  $Q_i$  refers to the normalized rate in bps/Hz of the  $i^{th}$  GW such that  $Q_i = \frac{q_i}{T}$  where  $q_i$  is the amount of data stored in the  $i^{th}$  GW, in bits, and T is the transmission time, a fixed time slot for the GWs.

# 4.2.2 Convexity Analysis

The objective function,  $P_{\text{Total}}$  is a linear function and is therefore a convex function. The first set of constraints on  $P_i, \forall i \in \{1, ..., N\}$  are linear constraints too. Thus, each one of them forms a convex set. The upper bounds on the normalized data are of the type  $\log(1 + ax + by) > c$  where a, b and c are constants. Since the log function is a concave function, these set of constraints represent a convex set. Hence, the problem is convex and we can solve it using the f mincon algorithm in MATLAB.

# 4.2.3 Proposition

The optimal decoding order at the DC for the problem in Eq. 4.2, that will minimize the total power expenditure, is to decode the signals of the GWs based on the channel value in descending order.

#### 4.2.4 Proof

Consider the last constraint on the sum of rates in Eq. 4.2, i.e.  $\sum_{i=1}^{N} Q_i \leq \log_2\left(1+\frac{\sum_{i=1}^{N} P_i|g_i|^2}{N_0}\right)$ . For minimum total power, it is obvious that the constraint should hold with equality. Let us call  $A=\sum_{i=1}^{N} Q_i$ , where A is a constant. Assume the channel values  $g_i, \forall i \in 1, ..., N$  are ordered in a descending order, and assume  $P_{N,\min}$  is the minimum possible value for  $P_N$ , such that,

$$A = P_1|g_1|^2 + \dots + P_{N-1}|g_{N-1}|^2 + P_{N,\min}|g_{N-1}|^2$$
(4.3)

Now, let us subtract  $\Delta_1$  from  $P_1$  and add  $\Delta_N$  to  $P_{N,\min}$  such that the equality still holds, where,

$$A = (P_1 - \Delta_1)|g_1|^2 + \dots + P_{N-1}|g_{N-1}|^2 + (P_{N,\min} + \Delta_N)|g_{N-1}|^2$$
(4.4)

where  $\Delta_N |g_N|^2 = \Delta_1 |g_1|^2$ . Therefore,  $\Delta_1 = \Delta_N \frac{|g_N|^2}{|g_1|^2} < \Delta_N$ . The total power in this case is,

$$P_{\text{Total}} = P_1 - \Delta_1 + \dots + P_{N-1} + P_{N,\min} + \Delta_N$$

$$= P_1 + \dots + P_{N-1} + P_{N,\min} + (\Delta_N - \Delta_1)$$

$$> P_1 + \dots + P_{N-1} + P_{N,\min},$$
(4.5)

since  $\Delta_N - \Delta_1$  is a positive term. Hence, we need to use the minimum value for  $P_N$  by decoding it last. By repeating the same procedure for  $P_{N-1}$  up to  $P_1$ , we find that the decoding order should follow the decreasing order of the channel gain values.

#### 4.2.5 Problem 2 Formulation

In this problem the delivery of the stored data in the buffers of the GWs to the DC is considered again. The objective of this problem is to minimize the maximum transmission power of the GWs. The problem is formulated as a minimax problem, where the variables of optimization are the individual transmission powers of the GWs and the decoding order at the DC. The GWs should transmit all their data

because the buffers are limited, so they can receive new information from the GPs in the next time slot. The set of all possible combinations of upper bounds on the rates form constraints on the normalized data. For practical consideration, each GW can send with power that is bounded by a maximum value,  $P_{max}$ . The problem is shown below,

$$\min_{\substack{P_i, \forall i \\ \text{Decoding order}}} \max_{i, \forall i} P_i \quad \text{subject to}$$

$$0 \le P_i \le P_{max}$$

$$\sum_{i \in W} Q_i \le \log_2 \left( 1 + \frac{\sum_{i \in W} P_i |g_i|^2}{N_0} \right),$$
(4.6)

where P is the power, W is the group of all possible combinations  $\binom{N}{b}$ ,  $\forall b \in \{1,...,N\}$ . Here,  $Q_i$  refers to the normalized rate in bps/Hz of the  $i^{th}$  GW such that  $Q_i = \frac{q_i}{T}$  where  $q_i$  is the amount of normalized data stored in the  $i^{th}$  GW, in bits/Hz, and T is the transmission time, which is a fixed-size time slot for the GWs.

# 4.2.6 Convexity Analysis

Similar to the first problem, we prove here the convexity of problem 2. The objective function,  $\max P_i$  is a linear function and is therefore a convex function. The first set of constraints on  $P_i, \forall i \in \{1, ..., N\}$  are linear functions and so they form a convex set. The upper bounds on the normalized data are similar to  $\log(1 + ax + by) > c$  where a, b and c are constants. Since the log function

is a concave function, these set of constraints form a convex set. Therefore, the problem is convex.

# 4.2.7 Time Sharing between Decoding Order Combinations

A possible scenario that the DC is going to apply to achieve power fairness is to use time sharing between two or more decoding order combinations. For time sharing between two decoding order combinations, the sum-rate will be the maximum value and its point will lie on the line connecting between the two corners in the capacity region characterized in Eq. 3.4. To achieve any point on the line, the DC will alternate between the two corners by giving a weight to each decoding order characterized by the corner. This may sometimes prove useful to achieve power fairness, by working at a point where the maximum power of the GWs will be less than the value achieved by working at any of the individual decoding order combinations. A system of linear equations is solved to find the exact percentage of time for each decoding order at which the DC should work to achieve the goal point. This will be clear in the examples that will follow.

#### 4.2.8 Results

The two problems are solved using the algorithm *fmincon* in MATLAB. *fmincon* algorithm utilizes a number of techniques to solve convex optimization problems. These techniques include interior-point method and sequential quadratic

programming (SQP). These methods are based on approximation of the nonlinear constraints using linear approximations. For our results here we choose SQP. A number of examples for different number of GWs N, sets of stored data Q and channel gain values G are presented and the optimal power values for each GW as well as the optimal decoding order at the DC are shown. The total power is also calculated for each example. The channels and stored data are the same in each example for problem 1 and problem 2. This is done to make it easy to compare the results for the two problems and to draw conclusions.

#### • Example 1

In this example three GWs are considered. The normalized stored data in the buffer of each GW and the channel gain value between the GWs and the DC are given below,

$$Q = [0.6 \quad 0.2 \quad 0.8],$$

$$G = [0.3 \quad 0.7 \quad 0.4],$$

where Q is in bps/Hz. Solving the min-total-power problem, the individual powers for the GWs are found to be,

$$P_1 = 5.73W$$
  $P_2 = 0.801W$   $P_3 = 7.021W$ ,

and the total power,  $P_{\text{Total}} = 13.552W$ . The optimal decoding order at the DC is found to be:  $GW_2$  then  $GW_3$  then  $GW_1$ . However, for the second

problem, the solution is found by setting the powers of the GWs to be,

$$P_1 = 6.5561W$$
  $P_2 = 0.801W$   $P_3 = 6.5561W$ ,

and the total power,  $P_{\text{Total}} = 13.913W$ . We notice that in this case the decoding is done by decoding  $GW_2$  and then doing time sharing between  $GW_3$  and  $GW_1$ . This can be seen by looking at the upper bounds on the achievable rates that hold with equality. We find that only two inequalities hold with equality which are,

$$Q_1 + Q_3 \le \log_2 \left( 1 + \frac{P_1|g_1|^2 + P_3|g_3|^2}{N_0} \right)$$

$$Q_1 + Q_2 + Q_3 \le \log_2 \left( 1 + \frac{P_1|g_1|^2 + P_2|g_1|^2 + P_3|g_3|^2}{N_0} \right)$$

By subtracting the sum inequality from the other one, we find that the first GW to be decoded is  $GW_2$ . The exact percentage of time sharing between the other GWs can be found by solving any of the following equations for  $\mu$ ,

$$Q_1 = \mu R_{11} + (1 - \mu) R_{12},$$

$$Q_2 = \mu R_{31} + (1 - \mu) R_{32},$$

where  $R_{11}$  is the rate for  $GW_1$  when the DC decodes  $GW_1$  then  $GW_3$ ,  $R_{12}$  is the rate for  $GW_1$  when the DC decodes  $GW_3$  then  $GW_1$  and similarly for

 $R_{31}$  and  $R_{32}$ . However,  $R_{31}$  and  $R_{32}$  refer to the rate of GW<sub>3</sub>. In this case,  $\mu$  is 0.227, so the decoding will be 22.7% of the time that the DC will decode GW<sub>1</sub> then GW<sub>3</sub> and 77.29% of the time in the opposite direction.

#### • Example 2

Four GWs are considered in this example. The normalized stored data in the buffer of each GW and the channel gain value between the GWs and the DC are given below,

$$Q = [0.39 \quad 1.44 \quad 1.44 \quad 1.76],$$

$$G = [1.13 \quad 1.80 \quad 0.60 \quad 1.83],$$

where Q is in bps/Hz. Solving the problem of the min-total power, the individual powers for the GWs are found to be,

$$P_1 = 0.665W$$
  $P_2 = 1.884W$   $P_3 = 4.724W$   $P_4 = 6.702W$ ,

and the total power,  $P_{\text{Total}} = 13.975W$ . The optimal decoding order at the DC is found to be:  $GW_4$  then  $GW_2$  then  $GW_1$  and finally  $GW_3$ .

However, for the second problem, the solution is found by setting the powers of the GWs to be,

$$P_1 = 1.707W$$
  $P_2 = 4.04W$   $P_3 = 4.72W$   $P_4 = 4.28W$ ,

and the total power,  $P_{\text{Total}} = 14.749W$ . We notice that in this case the decoding is done by decoding  $GW_1$  and then  $GW_2$  then  $GW_3$  and finally  $GW_4$ .

#### • Example 3

This example depicts eight GWs. The normalized stored data in the buffer of each GW and the channel gain value between the GWs and the DC are given below,

$$Q = \begin{bmatrix} 0.996 & 1.389 & 1.669 & 1.219 & 1.149 & 0.652 & 0.913 & 1.428 \end{bmatrix},$$
  $G = \begin{bmatrix} 1.095 & 0.524 & 2.220 & 0.967 & 1.236 & 1.480 & 1.837 & 0.602 \end{bmatrix},$ 

where Q is in bps/Hz. Solving the first problem which is the min-total power, the individual powers for the GWs are given as,

$$P_1 = 13.61W$$
  $P_2 = 5.893W$   $P_3 = 94.85W$   $P_4 = 10.02W$   $P_5 = 26.11W$   $P_6 = 18.88W$   $P_7 = 29.85W$   $P_8 = 12.20W$ ,

and the total power,  $P_{\text{Total}} = 211.405W$ . The optimal decoding order at the DC is found to be:  $GW_3$  then  $GW_7$  then  $GW_6$  then  $GW_5$  then  $GW_1$  then  $GW_4$  then  $GW_8$  and finally  $GW_2$ .

However, for the second problem, the solution is found by setting the powers

of the GWs to be,

$$P_1 = 46.057W$$
  $P_2 = 46.057W$   $P_3 = 46.057W$   $P_4 = 46.057W$   $P_5 = 46.057W$   $P_6 = 46.057W$   $P_7 = 46.057W$   $P_8 = 46.057W$ ,

and the total power,  $P_{\text{Total}} = 368.46W$ . In this case, the DC is doing time sharing to achieve power fairness. The power values are all equal and this is the best possible solution as any decrease of a power value will prompt an increase in another to satisfy the upper bounds constraints. The only upper bound constraint that holds with equality is the total sum-inequality, and this shows that the DC will do time sharing between a number of decoding order combinations. A system of eight equations and eight variables is solved to find the exact percentage for each decoding order that the DC will use. The decoding order combinations can be chosen randomly but if one or more of the variables is negative, this means that the target point is out of the targeted area. In this case, the decoding order associated with that variable has to be flipped. The decoding order combinations are found to be:

$$GW_1 \rightarrow GW_2 \rightarrow GW_3 \rightarrow GW_4 \rightarrow GW_5 \rightarrow GW_6 \rightarrow GW_7 \rightarrow GW_8 \text{ with } 22.38\%$$

$$GW_7 \rightarrow GW_6 \rightarrow GW_5 \rightarrow GW_4 \rightarrow GW_3 \rightarrow GW_2 \rightarrow GW_1 \rightarrow GW_8 \text{ with } 3.11\%$$

$$GW_7 \rightarrow GW_8 \rightarrow GW_1 \rightarrow GW_2 \rightarrow GW_3 \rightarrow GW_4 \rightarrow GW_5 \rightarrow GW_6 \text{ with } 5.94\%$$

$$GW_6 \rightarrow GW_7 \rightarrow GW_8 \rightarrow GW_1 \rightarrow GW_2 \rightarrow GW_3 \rightarrow GW_4 \rightarrow GW_5 \text{ with } 15.36\%$$

$$GW_5 \rightarrow GW_6 \rightarrow GW_7 \rightarrow GW_8 \rightarrow GW_1 \rightarrow GW_2 \rightarrow GW_3 \rightarrow GW_4 \text{ with } 14.77\%$$

 $GW_4 \rightarrow GW_5 \rightarrow GW_6 \rightarrow GW_7 \rightarrow GW_8 \rightarrow GW_1 \rightarrow GW_2 \rightarrow GW_3$  with 20.93%  $GW_3 \rightarrow GW_4 \rightarrow GW_5 \rightarrow GW_6 \rightarrow GW_7 \rightarrow GW_8 \rightarrow GW_1 \rightarrow GW_2$  with 1.14%  $GW_2 \rightarrow GW_3 \rightarrow GW_4 \rightarrow GW_5 \rightarrow GW_6 \rightarrow GW_7 \rightarrow GW_8 \rightarrow GW_1$  with 16.37%

# 4.3 Gateways Equipped with Large Buffers

In this section we assume that the buffers of the GWs are occupied with long queues of data that have been previously received. Data delivery from the GWs to the DC is studied and an optimization problem is formulated to maximize the weighted sum of the achievable rates of the GWs. The convexity of the problem is studied and proved. Results based on simulation are shown for several examples. Finally, with final remarks the chapter is concluded.

#### 4.3.1 Problem 3 Formulation

The objective of this problem is to maximize the weighted sum of the rates of the GWs. Each GW will enjoy a rate that is proportional to its buffer size. The longer the queue of data in the buffer, the larger is the weight in the objective function. A constraint of maximum power is held on the total power of the GWs. Thus, the problem is to allocate the powers for each GW such that the objective function is maximized. A set of constraints that is comprised of all the combinations of upper bounds on the rates are put also on the objective function. The problem

mathematical formulation is shown as,

$$\max_{P_{i},\forall i} \sum_{i=1}^{N} w_{i} R_{i} \quad \text{subject to}$$

$$0 \leq P_{\text{Total}} \leq P_{max}$$

$$\sum_{i \in W} R_{i} \leq \log_{2} \left(1 + \frac{\sum_{i \in W} P_{i} |g_{i}|^{2}}{N_{0}}\right),$$
(4.7)

where  $w_i$  is the normalized weight of the  $i^{th}$  buffer and all the weights sum to one,  $\sum_{i=1}^{N} w_i = 1.$  The total power  $P_{\text{Total}} = \sum_{i=1}^{N} P_i$ , which is the sum of all powers of the GWs. As can be seen in the objective function, the larger is the queue of a buffer of a certain GW, the more weight it will get.

# 4.3.2 Convexity Analysis

As we have seen, this problem is formulated as a maximization problem. The objective function is a linear function and is therefore a concave function. The first constraint on  $P_{\text{Total}}$  is a linear function and so it forms a convex set. The upper bounds on the normalized data are similar to  $\log(1 + ax + by) > c$  where a, b and c are constants. Since the log function is a concave function, these set of constraints form a convex set. Therefore, the problem is convex.

#### 4.3.3 Discussion

In this problem, the queues of the buffers are assumed to be large. This is because the time slot is assumed to be equal in size for all transmission sessions. When the stored data in the buffers is small in size such that all the data can be sent within the time slot, a different problem will appear. The GW that has higher rate will finish sending its data faster and then it will have zero rate. When this happens, the upper bounds on the achievable rates will be altered as the rate of some of the GWs will be zero at some point during the transmission period. That is why we limit our problem to the type of buffers that are filled with large queues of data. In this case, all the upper bounds on the achievable rates will hold throughout the transmission time.

#### **4.3.4** Results

Three examples are given, where in the first example a network of three GWs are considered. The second example considers a network of five GWs and the last example considers a network of eight GWs. In each network, random values for the normalized stored data in the buffers are generated. Also, random realizations of the channels between the GWs are generated following the Rayleigh distribution model given in Eq. 2.1. The individual powers for the GWs as well as the optimal decoding order are presented.

#### • Example 1

In this example a network of three GWs is considered. The normalized stored data in the buffer of each GW and the channel gain value between the GWs and the DC is given below,

$$Q = [25.53 18.13 32.97],$$

$$G = [0.479 \quad 2.473 \quad 0.750],$$

where Q is in bps/Hz. Q is generated from the uniform distribution between 30 and 100 i.e.  $\in [30, 100]$ . The problem is solved using the fmincon algorithm, where SQP is used. The maximum total power is set to be  $P_{max} = 100W$ . From the given Q, the weights for each buffer are calculated to be

$$W = [0.333 \quad 0.234 \quad 0.43],$$

where  $\sum_{i=1}^{3} W_i = 1$ . The individual powers for the GWs that will maximize the objective function are found to be,

$$P_1 = 0W$$
  $P_2 = 51.318W$   $P_3 = 48.68W$ ,

and the total power,  $P_{\text{Total}} = 100W$ . The optimal decoding order at the DC is found to be:  $GW_2$  then  $GW_3$  while  $GW_1$  is turned off. The normalized rate for each of the  $GW_3$  is found to be,

$$R = [0 \quad 3.59 \quad 4.828],$$

Note that the GW that has lower channel value is turned off as its effect

on maximizing the weighted sum of the rates is less compared to the other GWs. The other two GWs share the total powers.

#### • Example 2

In this example a network of five GWs is considered. The normalized stored data in the buffer of each GW and the channel gain value between the GWs and the DC is given below,

$$Q = [61.39 \quad 25.28 \quad 23.29 \quad 52.85 \quad 91.73],$$

$$G = \begin{bmatrix} 0.241 & 2.029 & 1.740 & 0.880 & 0.442 \end{bmatrix},$$

where Q is in bps/Hz. Q is also generated using the uniform distribution between 30 and 100, i.e.  $\in$  [30, 100]. The problem is solved using the fmincon algorithm, where SQP is used. The maximum total power is set to be  $P_{max} = 1000W$ . From Q, the weights for each buffer are calculated to be

$$W = [0.241 \quad 0.099 \quad 0.0915 \quad 0.2076 \quad 0.3604],$$

where  $\sum_{i=1}^{5} W_i = 1$ . The individual powers for the GWs that will maximize the objective function are found to be,

$$P_1 = 0W \quad P_2 = 207.45W \quad P_3 = 0W$$

$$P_4 = 226.479W$$
  $P_5 = 566.07W$ ,

and the total power,  $P_{\text{Total}} = 1000W$ . The optimal decoding order at the DC is found to be:  $GW_2$  then  $GW_4$  then  $GW_5$  while  $GW_1$  and  $GW_3$  are turned off. The normalized rate for each of the  $GW_5$  is found to be,

$$R = \begin{bmatrix} 0 & 1.994 & 0 & 1.356 & 6.805 \end{bmatrix},$$

Here,  $GW_1$  which has the lowest channel value is turned off and also  $GW_3$  which has the lowest stored normalized data is also turned off. The other three  $GW_5$  share the total powers where the GW with the largest weight,  $GW_5$  get the largest share. Also, the optimal decoding order is such that  $GW_5$  is decoded last and gets maximum possible rate.

#### • Example 3

In this example a network of eight GWs is considered. The normalized stored data in the buffer of each GW and the channel gain value between the GWs and the DC is given below,

$$Q = [87.12 \quad 13.91 \quad 72.25 \quad 98.11 \quad 35.49 \quad 22.04 \quad 71.68 \quad 91.85],$$
  $G = [0.610 \quad 1.260 \quad 1.920 \quad 1.280 \quad 0.870 \quad 0.560 \quad 1.810 \quad 1.560],$ 

where Q is in bps/Hz. Q is generated following the uniform distribution between 30 and 100, i.e.  $\in$  [30, 100]. The problem is solved using the fmincon algorithm, where SQP is used. The maximum total power is set to be  $P_{max} = 5000W$ . From Q, the weights for each buffer are calculated to be

$$W = \begin{bmatrix} 0.177 & 0.0282 & 0.147 & 0.199 & 0.072 & 0.0448 & 0.1456 & 0.1865 \end{bmatrix},$$

where  $\sum_{i=1}^{8} W_i = 1$ . The individual powers for the GWs that maximize the objective function are found to be,

$$P_1 = 67.88W$$
  $P_2 = 0W$   $P_3 = 1693.9W$   $P_4 = 692.826W$   $P_5 = 0W$   $P_6 = 0W$   $P_7 = 1331.3W$   $P_8 = 1214.1W$ ,

and the total power,  $P_{\text{Total}} = 5000W$ . The optimal decoding order at the DC is found to be:  $GW_7$  then  $GW_3$  then  $GW_1$  then  $GW_8$  then  $GW_4$  while  $GW_2$ ,  $GW_5$  and  $GW_6$  are turned off. The normalized rate for each of the  $GW_8$  is found to be,

$$R = [0.0087 \quad 0 \quad 1.33 \quad 10.146 \quad 0 \quad 0 \quad 0.5047 \quad 1.853],$$

In this case, GW<sub>2</sub> which have the lowest channel value and lowest stored normalized data is turned off. Also, GW<sub>5</sub> and GW<sub>6</sub> which have relatively low channel values and stored normalized data are turned off.

# 4.4 Concluding Remarks

In this chapter the data delivery from a set of GWs towards the DC is studied and modelled. Two types of buffers at the GWs are considered. The first type is a small-size buffer which is suitable for the reception of only one set of data from the GPs. Two problems are formulated for this case. The first problem's objective is to minimize the total power consumed by the GWs. The second problem is a power fairness problem, where the objective is to minimize the maximum power of transmission of all the GWs. Both problems differ in the objective function only, whereas the constraints are similar. The constraints are practical constraints on the individual powers of the GWs and all the possible combinations of upper bounds on the achievable rates of the GWs. Results are listed as three examples that share the same input information. The normalized stored data in each buffer and the channel gain value between the GWs and the DC are generated randomly. Results show that the min-total power problem is solved using normal SIC procedure, where the DC decodes a GW signal and then subtracts it from the sum-signal. However, while solving the min-max power the DC may use time sharing in the decoding process, where it will alternate between corners of the capacity region in order to achieve the maximum sum-rate while featuring fairness between the powers of the GWs. The second type of buffers at the GWs is large buffers store long queues of data. In this case, the problem is formulated to maximize the weighted-sum of the GWs' rates. This will let each GW transmit with a rate that is proportional to its storage of data, so the GW with longer

queue will enjoy more rate. The convexity of the problem is proved, and *fmincon* algorithm is used to find the best distribution of the powers and the optimal decoding order at the DC. It is found that the GW which have lower channel gain value and/or lower data storage may get smaller share as expected, or even get turned off i.e. its power is zero.

### CHAPTER 5

## **CONCLUSION**

In this chapter, the conclusion and future work are shown. The conclusion is based on the major contributions of this work. This includes system modelling, maximization of the sum-rate of the GPs and the delivery of data from the GWs to the DC. Based on details from this work and opportunities in the field, the future work is presented which helps interested researchers to find promising areas of research.

#### 5.1 System Modelling

The seismic acquisition system is modelled as a communication system with two transmission stages. The first stage includes a set of GPs as multiple sources of data. The GPs sample their data and encode them using Gaussian codes. The channels are assumed to be Rayleigh block-fading that remain constant for an interval of time and change randomly between time slots. A few GWs are considered as multiple destinations at the first stage. The GW is equipped with

a buffer to store data. The second stage is the GWs and the DC, where the GWs are the sources of data now. The DC is the destination and it receives data from the GWs and is assumed to have an infinite buffer so that it never overflows. This system model offers area for theoretical study of the seismic acquisition system, which is described in the following sections.

#### 5.2 Maximizing Sum-Rate of the GPs

In the first stage we consider the problem of the maximization of the sum-rate of the GPs. The problem is formulated as an integer programming problem, where the links between a GP and a GW has a binary index. This index assumes one when the GW decides to decode the signal of the GP using SIC. The selection process of the GPs at each GW is shown to have a big effect on the final sumrate. This optimization problem creates a large search space that is hard to fully explore in short time. Thus, metaheuristic algorithms are studied and adapted for the problem. Five metaheuristic algorithms are proposed based on theories from social science and material science. It is found that all the proposed algorithms give comparable results to the optimal solution found using ES. However, when the dimensions of the network gets larger, the search space increases exponentially and it is infeasible to find the optimal solution. In this case, the algorithms' performance is measured with respect to the case of no optimization. The case of no optimization is when the GWs decode all the signals from the GPs without any selection. In this case, more bounds are put on the achievable rates which

lower them. Given a limited computational budget, it is found that AS achieves the best sum-rate in a limited time.

#### 5.3 Data Delivery from the GWs to the DC

After that, the problem of delivering the data stored in the GWs was considered and studied. Two types of buffers at the GW are realized depending on the length of the buffer. Small buffers that are suitable for the reception and transmission of one set of data is considered first. Two problems are formulated for a system with small-size buffers at the GWs. The first problem considers the minimization of the total power expenditure of the GWs. This is subject to constraints on the individual powers of the GWs and for upper bounds on all combinations of the achievable rates. The variables of the optimization problem are the individual powers of the GWs and the decoding order at the DC. It is proposed that the optimal decoding order at the DC is the descending order of the channel gain values and this is proved next. Furthermore, the problem is studied for convexity and solved using fmincon algorithm. Results show an agreement between the proposition and the simulation results. The second problem considers the minimization of the maximum transmission power of the GWs. This problem aims at finding the power distribution and decoding order to achieve fairness between the power values of the GWs. The solution is found by simulating the convex problem using the fmincon algorithm. This shows that sometimes a time sharing approach of decoding is the best way to achieve power fairness.

Large buffers at the GWs are studied next. The buffers are assumed to be filled with long queues of data. Maximizing the weighted sum of the rates of the GWs is proposed as an optimization problem. In this case, the total power of the GWs is constrained by a maximum threshold. The objective is to find the distribution of the powers of the GWs and the decoding order at the DC. Using convex optimization tools, the problem is solved and simulated using the fmincon algorithm. It is found that the GWs which have larger weight may enjoy larger rate by taking larger share of the total power and by getting decoded later. On the other hand, GWs with less weight may get lower power or even be turned off.

#### 5.4 Future Work

Based on the study of the problems that were discussed in this work, several possible extensions of the work are presented in this section. Also, some opportunities are listed which are close to this area of research. Based on the literature survey, the wireless seismic acquisition system is still under-researched in the theoretical aspects of system performance. Past works are focusing on the wireless technologies to be employed and are directed towards practical side of the system performance. As a future work it is suggested to study the sum-rate using another decoding method such as joint decoding. Also, it is possible to extend the two-stage delivery system into a multiple stage system. This case is more practical as some GPs will send to other GPs before transmitting to the GWs. These GPs that are on the receiving end are known as leaf nodes [8]. A multi stage system

differs from the two-stage system and requires different perspective. Also, it is possible to consider different link selection and activation schemes from the one we propose. A possible scenario, for example, is the simultaneous activation of a single link in the first stage and another link in the second stage. However, if the transmission is assumed to be half-duplex, the GW that receives should be different from the GW that sends.

As we have seen, metaheuristic algorithm suffer from slow convergence when the search space gets larger. We adapted the heuristic aspect of the ACO algorithms to increase their speed of convergence and achieve higher results. However, the SA algorithm still suffers from this disadvantage. A possible extension is to find a method that will mitigate the stagnation that SA suffers from. This invites an unconventional look at the algorithm, as simple changes of the parameters did not work. Another possible extension of the work is to study the case of second-stage data delivery, where some of the GWs, that are equipped with large buffers, run out of data to send during the transmission period. As we have seen, this will change the optimization problem as some of the constraints are not applicable anymore. In this case, the GWs that run out of data will be turned off. Thus, their effect of interference is removed and therefore some upper bounds on the achievable rates may be altered. This can be an interesting problem to study too. Another possible problem is to study the fairness of transmission time at the second stage. The GW that have higher rate may finish first and thus its share of interference will be removed from the network. This will change the set of upper

bounds on the achievable rates.

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