Real-time Resource Management and Energy Trading for Green Cloud-RAN

Wan Ariffin, Wan Nur Suryani Firuz

Awarding institution:
King's College London

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Real-time Resource Management and Energy Trading for Green Cloud-RANs

Wan Nur Suryani Firuz Bt Wan Ariffin

A thesis submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

of

King’s College London.

Centre for Telecommunications Research
King’s College London

August 8, 2017
To my beloved husband, children, parents, mother in law and all family members.
Abstract

This thesis considers cloud radio access network (C-RAN), where the remote radio heads (RRHs) are equipped with renewable energy resources and can trade energy with the grid. Due to uneven distribution of mobile radio traffic and inherent intermittent nature of renewable energy resources, the RRHs may need real-time energy provisioning to meet the users demands. Given the amount of available energy resources at RRHs, the main contributions of the thesis begin with introducing real-time resource management strategies to the RRHs with a shortage of power budget to select an optimal number of user terminals based on their available energy budget. On the other hand, sparse beamforming strategies introduced in the second part of the thesis account for all RRHs with or without a shortage of power and take consideration of realistic constraints on fronthaul capacity restrictions. The proposed strategies strike an optimum balance among the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, RRHs total transmit power and the maximum or total spot-market energy cost. A smart energy management strategy based on the combinatorial multi-armed bandit (CMAB) theory for C-RAN, which is powered by a hybrid of grid and renewable energy sources is studied in the last part of the thesis. A combinatorial upper confidence bound (CUCB) algorithm to maximize the overall rewards, earned as a result of minimizing the cost of energy trading at individual RRHs of the C-RAN has been introduced. Adapting to the dynamic wireless channel conditions, the proposed CUCB algorithm associates a set of optimal energy packages, to be purchased from the day-ahead markets, to a set of RRHs to minimize the total cost of energy purchase from the main power grid by dynamically forming super arms. A super arm is
formed on the basis of calculating the instantaneous energy demands at the current time slot, learning from the cooperative energy trading at the previous time slots and adjusting the mean rewards of the individual arms.
Acknowledgements

First and foremost, I would like to thank my Lord who gave me the strength and the means to embark upon the journey to my PhD.

This thesis would not have been possible without the guidance and the support of several individuals who helped me along this most unforgettable experiences of my life. I am sincerely grateful to my primal supervisor Dr. Mohammad Reza Nakhai one of the most amazing personalities that I have come across in my life. He provided a unique perspective on novel research directions and taught me to maintain my integrity as a researcher. Indeed, he is an irreplaceable asset for King’s College London.

My sincere gratitude is reserved for my thesis and VIVA voce examiners, Associate Professor Dr. Soon Xin Ng (University of Southampton) and Professor Muhammad Ali Imran (University of Glasgow) for their invaluable insights and suggestions. I remain amazed that despite their busy schedules, they were able to go through the final draft of my thesis within a few weeks with extremely useful comments and suggestions.

Furthermore, I would like to express my appreciation to Professor Mischa Dohler and Professor Hamid Aghvami (former), head of Centre of Telecommunication Research (CTR) department, for their vision, sagacity, and enthusiasm for innovation. I am particularly grateful to my colleagues at CTR, including Sarah, Sumayyah Dzulkifly, Hessa Alfraihi, Sunila Akbar, Nasreen Anjun, Halen, Hong, and many others, who have convinced me that working hard is not incompatible with having fun. Especially, I would like to acknowledge the efforts of my best friends, Sumayyah Dzulkifly, Bibi Intan Suraya Murat, Nazahah Mustafa, Nur
Farhan Kahar, Nurfarah Athirah, and my team partner, Sarah, who are always by my side during the tough times and helped me in improving the quality of this work.

Acknowledgments go to Universiti Malaysia Perlis (UniMAP) and Kementerian Pengajian Tinggi (KPT), Malaysia for their financial and all the support. The highest gratitude goes to the top managements of UniMAP and school of computer and communication engineering (SCCE). Special dedications also go to my colleagues at SCCE, especially Shima, Aini, Aznor, Hasneeza, Rohani, Norma and many others, who gave me hours of moral support and enjoyable time to finish my thesis writing. I would like to acknowledge the efforts of Junita Nordin and Hasliza A Rahim who helped me in improving the quality of this work by proofreading the thesis.

Special thanks to all my family who always believed in me and encouraged me to take on the most difficult of challenges in life. Thanks to my beloved husband, Zahirul Fahmi Bin Zaini, who holds a special place in my heart and my children, Nur Qalesya Humaira Binti Zahirul Fahmi, Nur Raudhah Mardhiah Binti Zahirul Fahmi, Nur Hidayah Sofea Binti Zahirul Fahmi, Nur Inas Insyirah Binti Zahirul Fahmi and Zahirul Iman Fathi Bin Zahirul Fahmi, the best gifts Allah has ever given me. I am especially thankful to my loving parents, Wan Ariffin Bin Wan Derahman and Fatimah Binti Mat Zin, my mother in law, Zainun Binti Rahim, my siblings, Wan Noorul Hafilah, Wan Mohammad Najdan, Wan Shafini, Wan Mohammad Hakiman, Wan Mohammad Alimin, Wan Mohammad Ariff, Wan Abdul Qahhar, Wan Nur Syuhada, Wan Abdul Azim, and all my family members for their selfless and boundless love all through the years. Their perpetual support is always there no matter how far I travel away from home, since the hearts of our family are intrinsically bound together. I dedicate this work to all my loves.
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<th>Definition</th>
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<tr>
<td>AAS</td>
<td>adaptive antenna system</td>
</tr>
<tr>
<td>AoA</td>
<td>angle of arrival</td>
</tr>
<tr>
<td>AoD</td>
<td>angle of departure</td>
</tr>
<tr>
<td>AP</td>
<td>arithmetic progression</td>
</tr>
<tr>
<td>BBU</td>
<td>baseband processing unit</td>
</tr>
<tr>
<td>BS</td>
<td>base station</td>
</tr>
<tr>
<td>CAPEX</td>
<td>capital expenditure</td>
</tr>
<tr>
<td>CDMA</td>
<td>code-division multiple access</td>
</tr>
<tr>
<td>CMAB</td>
<td>combinatorial multi-armed bandit</td>
</tr>
<tr>
<td>$CO_2$</td>
<td>carbon dioxide</td>
</tr>
<tr>
<td>CoMP</td>
<td>coordinated multipoint</td>
</tr>
<tr>
<td>CP</td>
<td>centralized cloud computing processor</td>
</tr>
<tr>
<td>CPRI</td>
<td>common public radio interface</td>
</tr>
<tr>
<td>C-RAN</td>
<td>cloud radio access network</td>
</tr>
<tr>
<td>CSI</td>
<td>channel state information</td>
</tr>
<tr>
<td>CUCB</td>
<td>combinatorial upper confidence bound</td>
</tr>
<tr>
<td>DoA</td>
<td>direction of arrival</td>
</tr>
<tr>
<td>DoD</td>
<td>direction of departure</td>
</tr>
<tr>
<td>DRRHC</td>
<td>Dynamic RRH-centric Clustering</td>
</tr>
<tr>
<td>e.g.</td>
<td>for example</td>
</tr>
<tr>
<td>ET</td>
<td>energy receiving terminal</td>
</tr>
<tr>
<td>ForCMAB</td>
<td>forward combinatorial multi-armed bandit</td>
</tr>
<tr>
<td>GSMA</td>
<td>Global Systems for Mobile communications Association</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>-------------</td>
<td>-------------------------------------------------------</td>
</tr>
<tr>
<td>ICI</td>
<td>inter-cell interference</td>
</tr>
<tr>
<td>i.i.d.</td>
<td>independent and identically distributed</td>
</tr>
<tr>
<td>i.e.</td>
<td>that is</td>
</tr>
<tr>
<td>IT</td>
<td>information receiving terminal</td>
</tr>
<tr>
<td>KKT</td>
<td>Karush-Kuhn-Tucker</td>
</tr>
<tr>
<td>LHS</td>
<td>left hand side</td>
</tr>
<tr>
<td>MAB</td>
<td>multi-armed bandit</td>
</tr>
<tr>
<td>MAC</td>
<td>medium access control</td>
</tr>
<tr>
<td>MBS</td>
<td>master base station</td>
</tr>
<tr>
<td>MIMO</td>
<td>multiple input multiple output</td>
</tr>
<tr>
<td>MISO</td>
<td>multiple input single output</td>
</tr>
<tr>
<td>NP</td>
<td>non-deterministic polynomial-time</td>
</tr>
<tr>
<td>OBSAI</td>
<td>open base station architecture initiative</td>
</tr>
<tr>
<td>OFDM</td>
<td>orthogonal frequency-division multiplexing</td>
</tr>
<tr>
<td>OFDMA</td>
<td>orthogonal frequency-division multiple access</td>
</tr>
<tr>
<td>OPEX</td>
<td>operating expense</td>
</tr>
<tr>
<td>PSD</td>
<td>positive semidefinite</td>
</tr>
<tr>
<td>QoS</td>
<td>quality of service</td>
</tr>
<tr>
<td>RAN</td>
<td>radio access network</td>
</tr>
<tr>
<td>RevCMAB</td>
<td>reverse combinatorial multi-armed bandit</td>
</tr>
<tr>
<td>RF</td>
<td>radio frequency</td>
</tr>
<tr>
<td>RRH</td>
<td>remote radio head</td>
</tr>
<tr>
<td>SAP</td>
<td>successful access probability</td>
</tr>
<tr>
<td>SDP</td>
<td>semidefinite programming</td>
</tr>
<tr>
<td>SDR</td>
<td>semidefinite relaxation</td>
</tr>
<tr>
<td>SINR</td>
<td>signal-to-interference-plus-noise ratio</td>
</tr>
<tr>
<td>SNR</td>
<td>signal-to-noise ratio</td>
</tr>
<tr>
<td>SWIPT</td>
<td>simultaneous wireless information and power transfer</td>
</tr>
<tr>
<td>ZMCSCG</td>
<td>zero mean circularly symmetric complex Gaussian</td>
</tr>
<tr>
<td>1G</td>
<td>first generation</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Definition</td>
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<tr>
<td>--------------</td>
<td>------------------------------------</td>
</tr>
<tr>
<td>2G</td>
<td>second generation</td>
</tr>
<tr>
<td>3G</td>
<td>third generation</td>
</tr>
<tr>
<td>3GPP</td>
<td>3rd Generation Partnership Project</td>
</tr>
<tr>
<td>4G</td>
<td>fourth generation</td>
</tr>
<tr>
<td>5G</td>
<td>fifth generation</td>
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</tbody>
</table>
List of Symbols

\[ w \] scalar \( w \)
\[ \mathbf{w} \] vector \( \mathbf{w} \)
\[ \mathbf{W} \] matrix \( \mathbf{W} \)
\[ |w| \] magnitude of \( w \)
\[ \mathbf{W}^* \] complex conjugate of \( \mathbf{W} \)
\[ \mathbf{W}^T \] transpose of \( \mathbf{W} \)
\[ \mathbf{W}^{\dagger} \] complex conjugate transpose of \( \mathbf{W} \)
\[ \text{tr}(\mathbf{W}) \] trace of \( \mathbf{W} \)
\[ \text{vec}(\mathbf{W}) \] vectorization of matrix \( \mathbf{W} \) which converts the matrix into an column vector by stacking the columns of the matrix \( \mathbf{W} \) on the top of one another
\[ \text{rank}(\mathbf{W}) \] rank of \( \mathbf{W} \)
\[ \min_{\mathbf{w}} \] minimizes all the elements of \( \mathbf{w} \)
\[ \text{s.t.} \] subject to
\[ \mathbf{W}_{i,j} \] the \((i, j)^{th}\) entry of \( \mathbf{W} \)
\[ \mathbb{E}(\cdot) \] expectation operator
\[ \mathbf{W} \succeq 0 \] \( \mathbf{W} \) is a positive semidefinite matrix
\[ \mathbf{W} \succeq \mathbf{X} \] \( \mathbf{W} - \mathbf{X} \) is a positive semidefinite matrix
\[ w \succeq 0 \] all elements of \( w \) are nonnegative
\[ w \succ 0 \] all elements of \( w \) are positive
\[ w \succeq x \] element-wise greater than or equal to
\[ w \succ x \] element-wise greater than
\[ \mathbb{C}^n \] sets of \( n \) dimensional complex vectors
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>( \mathbb{R}^n )</td>
<td>sets of ( n ) dimensional real vectors</td>
</tr>
<tr>
<td>( \mathbb{C}^{n \times m} )</td>
<td>sets of ( n )-by-( m ) dimensional complex matrices</td>
</tr>
<tr>
<td>( \mathbb{R}^{n \times m} )</td>
<td>sets of ( n )-by-( m ) real matrices</td>
</tr>
<tr>
<td>( \mathcal{CN}(\mu, \Gamma) )</td>
<td>circularly symmetric complex normal distribution with mean ( \mu ) and variance ( \Gamma )</td>
</tr>
<tr>
<td>( A \in B )</td>
<td>a set ( A ) is a subset of a set ( B ) which is all the elements of ( A ) are contained in a set of ( B )</td>
</tr>
<tr>
<td>( x \to a )</td>
<td>( x ) approaches ( a )</td>
</tr>
<tr>
<td>( | \cdot |_p )</td>
<td>( \ell_p )-norm of a vector</td>
</tr>
<tr>
<td>( | \cdot |_0 )</td>
<td>number of non-zero entries in the vector</td>
</tr>
<tr>
<td>( \mathbf{I} )</td>
<td>identity matrix with a suitable size</td>
</tr>
<tr>
<td>( \sum_{i = \min}^{\max} w_i )</td>
<td>summation of all the elements of ( w_i ) where a set ( i ) is limits from a minimum to a maximum values</td>
</tr>
<tr>
<td>( \sum_{i \in A} w_i )</td>
<td>summation of all the elements of ( w_i ) where a set ( i ) is a subset of a set ( A )</td>
</tr>
<tr>
<td>( = )</td>
<td>equal to</td>
</tr>
<tr>
<td>( \sim )</td>
<td>is similar to</td>
</tr>
<tr>
<td>( \approx )</td>
<td>approximately equal to</td>
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<tr>
<td>( \neq )</td>
<td>not equal to</td>
</tr>
<tr>
<td>( \geq )</td>
<td>greater than or equal to</td>
</tr>
<tr>
<td>( \leq )</td>
<td>less than or equal to</td>
</tr>
<tr>
<td>( \ll )</td>
<td>much less than</td>
</tr>
<tr>
<td>( \gg )</td>
<td>much greater than</td>
</tr>
<tr>
<td>( b^x )</td>
<td>the base ( b ) and the exponent ( x ), i.e., ( b^x ) is the product of multiplying ( x ) bases</td>
</tr>
<tr>
<td>( e^x )</td>
<td>the natural exponential function</td>
</tr>
<tr>
<td>( \log_b(x) )</td>
<td>the logarithm of ( x ) to base ( b )</td>
</tr>
<tr>
<td>( \mathcal{O}(\log x) )</td>
<td>big oh (( \mathcal{O} )) is a notation to give an upper bound on a function ( \log x )</td>
</tr>
</tbody>
</table>
| \( \text{diag}(x_1, \cdots, x_N) \) | a diagonal matrix with the diagonal entries given by \( x_1, \cdots, x_N \). Also can be written as \( \text{Bdiag}(\mathbf{0}_1 \cdots \mathbf{0}_i \cdots \mathbf{I}_n \cdots \mathbf{0}_N) \), where \( \mathbf{0}_i \) is an
$M \times M$ matrix with all-zero elements and $I_n$ is an $M \times M$ identity matrix

$J_s^{-1}$

the normalized energy unit, i.e., $J_s^{-1}$, is adopted in this thesis

and thus the terms 'power' and 'energy' are mutually convertible.

**List of Symbols for Energy Management Model**

$E_n$ the amount of renewable energy generated at the $n$-th RRH

$B_n^{[\text{ahead}]}$ the amount of energy that has been purchased from the
day-ahead market for the $n$-th RRH

$B_n^{[\text{real}]}$ the amount of energy that is necessary to be purchased from
the real-time market for the $n$-th RRH

$S_n$ the amount of excessive energy sold back to the grid by
the $n$-th RRH

$\pi^{[\text{renew}]}$ the price of generating per unit renewable energy

$\pi^{[\text{ahead}]}$ the price of purchasing per unit energy from the day-ahead market

$\pi^{[\text{real}]}$ the price of purchasing per unit energy from the real-time market

$\pi^{[\text{sell}]}$ the price of selling back per unit energy to the grid

$P_n^{[\text{total}]}$ the total energy consumption at the $n$-th RRH

$P_n^{[\text{Tx}]}$ the total transmit power at the $n$-th RRH

$P_n^{[\text{circuit}]}$ the non-transmission hardware circuit power consumption at the
$n$-th RRH

$B_n^{[\text{total}]}$ the total energy cost of all the RRHs in the green C-RAN

$P_n^{[\text{Tmax}]}$ the maximum transmit power allowance at the $n$-th RRH

$P_{CP}^{[\text{max}]}$ the maximum power provision at the CP

**List of Symbols for Downlink Transmission Model**

$N$ the number of RRHs

$M$ the number of antennas per RRH

$K_e$ the number of active ETs

$K_e^{[\text{idle}]}$ the number of idle ETs

$K_i$ the number of ITs
\[ \mathcal{L}_b = \{1, \cdots, N\} \] the set of indexes for the RRHs
\[ \mathcal{L}_e = \{1, \cdots, K_e\} \] the set of indexes for the active ETs and \( \mathcal{L}_e[^{\text{idle}}] = \{1, \cdots, K_e[^{\text{idle}}]\} \) is the set of indexes for the idle ETs
\[ \mathcal{L}_i = \{1, \cdots, K_i\} \] the set of indexes for the ITs.
\[ \mathcal{L} = \{1, \cdots, Z\} \] the set of indexes for the RRHs that are in the shortage of power
where \( \mathcal{L} \subset \mathcal{L}_b \)
\[ P_{[\text{budget}]}^z \] power budget at the \( z \)-th RRH
\[ C_{[\text{fronthaul}]}^z \] the fronthaul capacity consumption for link between the CP and the \( z \)-th RRH that is in power budget shortage
\[ C_{[\text{fronthaul}]}^n \] fronthaul capacity consumption for link between the CP and the \( n \)-th RRH
\[ \sum_{n \in \mathcal{L}_b} \left\{ B_n[^{\text{real}}] \right\} \] the overall real-time energy-purchase from the grid
\[ \max_{n \in \mathcal{L}_b} \left\{ B_n[^{\text{real}}] \right\} \] the maximum real-time energy-purchase from the grid
\[ \sum_{z \in \mathcal{L}} P_{[\text{Tx}]}^z \] the total transmit power of the RRHs with shortage of power budget
\[ \mathcal{G}[^{\text{coop}}] \] the number of total active cooperative links between the RRHs and the receiving terminals
\[ \sum_{n \in \mathcal{L}_b} P_n[^{\text{Tx}}] \] the total transmit power of all the RRHs
\[ \mathcal{G}_e[^{\text{ET}}] \] the total energy harvested by the \( e \)-th active ET
\[ \mathcal{G}_z[^{\text{ET-idle}}] \] the total amount of energy that can be harvested from surroundings by the \( z \)-th idle ET
Chapter 1

Introduction

1.1 Thesis Statement

To meet the ever-increasing mobile data traffic and to provide pervasive always-connected broadband packet services for next generation networks, base stations (BSs) are proposed to be installed more densely to provide higher capacity [1, 2]. However, inter-cell interference (ICI) has become more severe and may lead to the bottleneck of the network throughput. The operational costs of the network have also increased due to energy consumption by the growing number of BSs.

Cloud radio access network (C-RAN) has been regarded as a promising solution owing to its superiority in ICI mitigation, and reducing both the capital expenditure (CAPEX) and the operating expense (OPEX) of the network operator [3]. In the proposed C-RAN architecture, the conventional BSs are physically detached into two parts: baseband processing units (BBUs) that are grouped together as a centralized cloud computing processor (CP) for designing all the coordination and energy trading strategies, and the remaining remote radio heads (RRHs) that are in charge of all radio frequency operations [4]. The data of information receiving terminals (ITs) is available at the CP and will be delivered to the multiple collaborative RRHs via high-capacity low-latency fronthaul links such as optical fibre links. However, due to a large number of densely deployed distributed RRHs, each serving a time-varying number of receiving terminals in a highly dynamic wireless environment, the amount of energy demand by the wireless network operator from
the reliable source, i.e., grid will be highly variable and statistically unknown over different times of the day. As a result, the network operator may need real-time energy provisioning to meet all the receiving terminals’ demand, and may take a risk of losing the profit.

C-RAN with a green energy technology has become a promising alternative solution for powering next generation wireless networks. In this green C-RAN, a large number of RRHs are installed with energy harvesting devices, i.e., solar panels and wind turbines that are capable of harvesting energy from environmental sources with a lower cost since renewable energy generation is generally cheaper than electrical energy off the grid. However, the green energy supply is heavily dependent on the weather and the installation site. Thus, it is impossible to fully rely on the green sources for powering wireless networks.

With the advancing technologies in smart grid, each RRH with local renewable energy generation allows the implementation of two-way energy trading with the smart grid [5, 6]. In the case of insufficient renewable energy, an RRH can request an amount of deficit energy from the grid to maintain its reliable operation and alternatively can make a profit by selling an amount of excess energy to the smart grid on an agreed price.

1.2 Thesis Motivation

Provided that all the RRHs are equipped with renewable energy harvesters and implemented with two-way energy trading, [7] proposes a joint energy trading for full cooperation scheme in coordinated multipoint (CoMP) network, where the data of all the ITs is available at the CP and will be distributed to all RRHs for cooperative transmission via fronthaul links. However, the data circulation between the CP and the RRHs requires huge fronthaul signalling overhead when full coordination is enabled [8]. The design in [7] that takes no account of fronthaul capacity restrictions may lead to infeasible results in a practical scenario.

Consequently, C-RAN with limited fronthaul capacity has been investigated by the research community and sparse beamforming technique for partial cooperation
is proposed to address the issue. With the implementation of sparse beamforming technique in a downlink transmission, the CP then only needs to distribute the receiving terminal’s data to its serving RRHs. Motivated by the literature that sparse beamforming technique is commonly formulated as a $\ell_1$-norm optimization problem and handled with reweighted $\ell_1$-norm method introduced in [9], [10–14] propose dynamic sparse beamforming designs subject to quality of service (QoS) constraints for capacity-limited fronthaul links in the C-RAN. The authors in [10] integrate the aforementioned works with simultaneous wireless information and power transfer (SWIPT) concept and study the resource allocation algorithm. However, none of them take into account the renewable energy sources that can be further extended to a joint management of the resource allocation and energy trading for green communication. For the next generation networks, it will be imperative to search for energy-efficient and spectrum solutions to the resource allocation problems in the C-RAN system powered by the smart grid and renewable energy generation.

This thesis addresses the questions of how to determine the best serving set of RRHs and how to design the best network-wide beamformer for each of the receiving terminals, with the aims to minimize the total cost of the network operator and to address all the given constraints. In general, these problems involve both uncertainty and conflict of interest between the network operator and the RRHs, because the network operator wish to minimize the total cost by serving as many receiving terminals as possible, while from the RRHs’ perspective, serving more receiving terminals consume more power and fronthaul capacity. Therefore, it becomes essential to search for new mathematical solutions to find an optimal tradeoff between the total transmit power, receiving terminal rates, and the fronthaul capacity.

The first core objective of this thesis is to study the potential of the sparse beamforming technique in a joint cooperative resource management and energy trading problem, to address the stated challenge. In Chapter 3 and Chapter 4, different sparse beamforming strategies are introduced in a joint cooperative resource management and energy trading in green C-RAN, to scrutinize the advantages of this partial cooperation scheme. Specifically, Chapter 4 integrates the C-RAN sys-
tem with SWIPT concept and propose a joint energy trading and partial cooperation design based on two sparse beamforming strategies to account for limited-capacity fronthaul links in the green C-RAN. These strategies strike an optimum balance among the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, RRHs total transmit power and the maximum or total spot-market energy cost.

Motivated by an abstract idea of multi-armed bandit (MAB) problem, the second core objective is to investigate and establish the potential of the MAB framework in the proposed sparse beamforming design. The MAB is a class of sequential optimization problems, where, at each trial, a player pulls an arm from a given $J$ arms in order to get an instantaneous reward [15]. Each of the arms is being associated with independent and identically distributed (i.i.d.) stochastic rewards. The problem investigated in this thesis is categorized as a combinatorial MAB (CMAB) problem, where a super arm that consists of a set of $N$ arms, $N \subset J$ is played and the rewards of its relevant arms are observed individually in each trial [16]. In this thesis, each arm corresponds to the size of an energy package to be purchased for a RRH from the day-ahead market prior to the actual time of energy demand. At each trial, a set of $N$ RRHs may lose some rewards due to not selecting the best arm instead of the played arms, called as regret. The objective of this CMAB problem is to maximize the accumulated reward by observing the associated reward of new arms, known as exploration, while simultaneously optimizing the decisions among a set of arms based on existing knowledge, known as exploitation, in multiple trials [17]. The work in Chapter 5 introduces two iterative energy trading algorithms based on CMAB to search for a set of cost-efficient energy packages in ascending and descending order of package sizes without accounting for the wireless channel dynamic.

These solutions lead to the third core objective which is to develop an online learning algorithm to manage the variability and uncertainty to maintain cost-aware reliable operation in C-RAN. The proposed algorithm employs a CMAB model and minimizes the energy cost over a long time horizon at RRHs. The algorithm
preshedules a set of cost-efficient energy packages to be purchased from an ancillary energy market for the future time slots by learning both from the cooperative energy trading at previous time slots and exploring new energy scheduling strategies at the current time slot. This work is presented in Chapter 6.

1.3 Thesis Contributions

1.3.1 Contributions

The major contributions of this thesis lead to the design of a smart online learning system for real-time resource management and energy trading in green C-RANs with the smart grid. Some key outcomes and findings of this work are summarized below:

1. A joint cooperative resource management and two-way energy trading model for C-RANs using the dynamic clustering technique is firstly proposed in [18] and this technique is presented in Chapter 3. By controlling the number of RRHs which jointly serve an IT within the coverage area, the clustering technique can lessen the capacity requirements on the constrained-fronthaul links. This chapter introduced three different cooperative real-time energy trading strategies in C-RANs and applies a sparse beamforming technique to find the optimal trade-off between the degree of partial cooperation among the RRHs in serving the ITs and the total energy cost of the network operator.

2. Chapter 4 integrates a real-time energy trading strategy with SWIPT concept, where the RRHs simultaneously transfer information beams to ITs and energy beams to active energy receiving terminals (ETs). Since energy could be highly attenuated over a long distance propagation and in order to maintain the efficiency of SWIPT, an iterative authorization algorithm that allows only those ETs situated close enough to the RRHs to receive wireless energy is introduced. On the top of that, two sparse optimization problems have been formulated with more realistic scenarios where RRHs are constrained with limited fronthaul capacities. This work has been published in [19]. The
works that have integrated some other real-time energy trading strategies with SWIPT concept are published in [20] and [21].

Initially, Chapter 3 and Chapter 4 assume a set of fixed sizes of energy packages has been purchased from the day-ahead market without the process of monitoring the actual amount of energy consumption and energy generated at the renewable energy harvesters at the individual RRHs.

3. Chapter 5 which is published in [22] further extends the works in previous chapters to a learning-based practical approach modelled as a CMAB problem. The CP is assumed to have no initial knowledge of forthcoming power budget and energy consumption at the individual RRHs. With various sizes of energy packages which are offered in the day-ahead market, two algorithms are developed, namely, ForCMAB Energy Trading and RevCMAB Energy Trading, to determine a set of optimal sizes of the energy packages to be purchased for the RRHs on the basis of actual energy supply and demand, to further minimize the total energy cost of the network operator. The other research related to MAB problem is published in [23].

4. Adapting to the dynamic wireless channel conditions, Chapter 6 which is proposed in [24] develops a smart online learning system based on the CMAB problem for the green C-RANs. A combinatorial upper confidence bound (CUCB) algorithm is proposed to maximize the overall rewards, earned as a result of minimizing the cost of energy trading at individual RRHs of the C-RAN. The proposed CUCB algorithm associates a set of optimal energy packages, to be purchased from the day-ahead markets, to a set of RRHs to minimize the total cost of energy purchase from the main power grid by dynamically forming super arms. A super arm is formed on the basis of calculating the instantaneous energy demands at the current time slot, learning from the cooperative energy trading at the previous time slots and adjusting the mean rewards of the individual arms. The works in [25] and [26] have applied this concept in different problems and scenarios.
1.3. Thesis Contributions

1.3.2 List of Publications

The publications that are related to the contributions of this thesis are listed as follows:


1.4 Thesis Outline

The rest of this thesis is organized as follows. A background study and literature review of the works related to the proposed research topic are provided in Chapter 2. The aim of this chapter is to provide fundamental concepts and technical background studies that are required to understand the problem areas addressed in this thesis. Subsequently, the main contributions of the thesis are discussed in Chapters 3, 4, 5 and 6. In Chapter 3, three different cooperative real-time energy trading strategies in C-RANs are proposed to jointly minimize the energy consumption and the real-time energy trading, under the constraints of demand and supply power balancing at RRHs and quality of service satisfaction at user terminals. These strategies mainly focus on power-shortage management. Then, Chapter 4 integrates the C-RANs system with SWIPT by introducing an iterative authorization algorithm. In this chapter, two sparse optimization problems have been formulated with more realistic scenarios where RRHs are constrained with limited fronthaul capacities. Interestingly, Chapter 5 focus on the development of a learning-based practical approach modelled as the CMAB problem. With the aim to further reduce the total energy cost of the network operator, the new responsibility of the CP is to determine the set of optimal sizes of the energy packages to be purchased for the RRHs on the basis of actual energy supply and demand. On the top of that, Chapter 6 develops an online learning algorithm as a pre-scheduling mechanism to manage the variability
and uncertainty to maintain cost-aware reliable operation in CRANs. Finally the thesis is concluded and some interesting directions for future studies are pointed out in Chapter 7.
Chapter 2

Background Study

2.1 Introduction
This chapter comprehensively surveys recent advances in fronthaul-constrained cloud radio access networks (C-RANs) with renewable energy technologies, particularly major issues related to the impact of constrained fronthaul on quality of service (QoS) of receiving terminals, energy efficiency and spectral efficiency. Furthermore, this chapter provides technical background studies that are required to understand the problem area, especially semidefinite programming (SDP) and a linear antenna array used for beamforming which are addressed in the contribution chapters. The concepts presented in this chapter are beneficial to the developments of resource management and energy trading schemes between the C-RANs and the smart grid that will be introduced in Chapters 3, 4, 5 and 6.

2.2 Evolution of Cellular System
By fully utilizing static frequency planning or code-division multiple access (CDMA) techniques in the traditional cellular systems, inter-cell interference (ICI) can be evaded. Therefore, cooperative processing is not demanded in the traditional first, second and third generation (1G, 2G, 3G) of the cellular radio access networks (RANs) as presented in Figure 2.1. However, in the fourth generation (4G) of the cellular systems, which is based on the orthogonal frequency-division multiplexing (OFDM) technique, the ICI becomes severe due to the spectrum reuse in adjacent cells. Thus, cooperative processing is needed.
Joint processing for cooperative transmission in the coordinated multipoint (CoMP) networks is presented as in Figure 2.2 has shown its potential performance advantages in terms of ICI mitigation and improvement of system throughput, especially for dense deployment of base stations (BSs). CoMP supports joint process-
Green Cloud Radio Access Networks: A Recent Trend for CoMP

A recent emerging deployment trend for CoMP network is to physically detach the baseband processing units (BBUs) from conventional BSs and group them into a BBU pool, i.e., a centralized cloud computing processor (CP). The remaining radio units, i.e., remote radio heads (RRHs) with antennas located at the remote sites, are connected to the BBUs via high-capacity low-latency fronthaul links, e.g., optical fibre links. This promising network architecture known as C-RAN reduces both the capital expenditure (CAPEX), i.e., the cost of developing non-consumable parts for the C-RAN system, and the operating expense (OPEX), i.e., the ongoing cost for running the C-RAN system, of the network operator [28].

Renewable Energy Technologies for Green C-RANs

A study shows that the cellular networks consumed world-wide is approximately 60 billion kWh per year [29]. In fact, the BSs consumed 80% of the electricity in cellular networks. As a result, more than a hundred million tons of carbon dioxide (CO₂) per year has been produced and this figure is expected to double by the year 2020 [1, 29]. Aware of this important huge energy consumption problem, some methods for green communication has been studied in [30–33], particularly for maximizing the energy efficiency of wireless communication systems.

A method for maximizing the energy efficiency using closed-form power allocation technique is studied in [30]. With a minimum average throughput requirement, this method is proposed to be implemented for a point-to-point single carrier system. Meanwhile, the studies in [31–33] focus on energy efficiency in cellular
multi-carrier multi-user systems for both uplink and downlink communications and they proved the existence of a unique global maximum for the energy efficiency for different systems. On contrary, the studies in [34–36] designed the system by using multiple antennas to further maximize the energy efficiency. Power loading algorithms with collocated and distributed antennas techniques have been proposed in [34] and [35], respectively. Furthermore, [36] studies the effect of using a large number of transmit antennas in orthogonal frequency-division multiple access (OFDMA) systems.

With enormously increasing demand for mobile data and high data rates such as online high definition video streaming and video conferencing, the aggregated power requirements by user terminals may exceed the amount of power budget at each of the RRHs in the C-RAN systems. Hence, the mobile network operators may take a risk of losing the profit. One of the potential solutions to address this issue and maintain the green communication is by using local renewable energy generation [37–39]. It has been investigated that energy harvesting devices installed at the RRHs can harvest energy from natural renewable energy sources such as solar and wind. Therefore, C-RANs with renewable energy technologies can be self-sustained and energy-efficient in providing ubiquitous service coverage.

### 2.3.2 System Architecture of C-RANs with Renewable Energy Technologies

Equipping the RRHs with energy harvesting devices that can generate local renewable energy from environmental sources, e.g., solar and wind, green communications and energy trading have been considered as promising techniques to benefit both the environment and the network operators. As shown in Figure 2.3, the general architecture of a C-RAN with green technologies consists of four main components as follows

1. In a C-RAN system, the BBUs clustered as a BBU pool is placed at a centralized site. The BBUs operate as virtual BSs to process baseband signals as well as to optimize the radio resource allocation. Based on traffic-aware
2.3. Green Cloud Radio Access Networks: A Recent Trend for CoMP

scheduling of receiving terminals and the time-varying radio channels, the signal processing resources are dynamically allocated and the processing capability is adaptively reconfigured. Most signal processing functions are conducted in the BBU pool, therefore RRHs can be distributed in a large-scale scenario in a cost-efficient manner [1].

2. RRHs are another main components in a C-RAN that provide a high data rate for receiving terminals with a basic wireless signal coverage. Radio frequency (RF) signals are transmitted to the receiving terminals by the RRHs in the downlink transmission, while the baseband signals from the receiving terminals are forwarded to the BBU pool for centralized processing in the uplink transmission. Basically, the responsibilities of RRHs are to perform interface adaptation, filtering, RF amplification, up and down conversion, analog-to-digital conversion and also digital-to-analog conversion.
3. The link that connects the BBU pool and the RRH is known as fronthaul. The link can be in a form of wire or wireless connection and its typical protocols include the common public radio interface (CPRI) and the open base station architecture initiative (OBSAI) [40]. Ideal fronthaul without any constraints and non-ideal fronthaul with constraints are two types of fronthaul links in the C-RAN architecture [1]. It has been written in [41] that the traditional coaxial-based systems on cell towers or legacy cell towers are being completely overhauled and replaced by fiber for more capacity, longer-reach distance and cost efficiency. The ideal fronthaul for C-RANs is optical fiber communication without constraints because it can provide a high transmission capacity at the expense of high cost and difficult to deploy. On contrary, wireless fronthauls are cheaper and more flexible to deploy, at the expense of limited capacity and other constraints. Since the cost of wireless fronthaul or capacity-constrained optical fiber is cheaper than the ideal optical fiber, these technologies are anticipated to be prominent in practical C-RANs. In addition, these technologies are flexible to set up. This thesis focuses only on non-ideal capacity constrained fronthaul.

4. Powering radio RRH sites with renewable energy sources can reduce energy costs significantly and improve the energy efficiency. In fact, the renewable energy resources do not generate greenhouse gases such as carbon footprint or $CO_2$ because renewable energy is derived from resources that are regenerative. 25 leading telecoms including MTN Uganda and Zain, united under the Global Systems for Mobile communications Association (GSMA) started a program named "Green Power for Mobile" [42, 43]. The main objective of this program is to use renewable energy resources such as solar, wind or sustainable biofuels technologies to power new and existing off-grid BSs and BSs that are in bad-grid locations. By 2020, estimates indicate that the global telecom industry will deploy approximately 390,000 BSs that are off-grid, and 790,000 BSs that are in bad-grid locations [44]. By implementing this renewable energy technologies, approximately 150 million barrels of diesel
2.3. Green Cloud Radio Access Networks: A Recent Trend for CoMP

per annum can be saved and annual carbon emissions can be reduced up to 45 million tonnes [44].

2.3.3 System Structures of Green C-RANs

As illustrated in Figure 2.4, system structures of C-RAN can be classified into three main options depending on the fronthaul constraints and the different function splitting between BBUs and RRHs. The three main options are full centralization structure, partial centralization structure and hybrid centralization structure.

![System structures of a C-RAN](image)

*Figure 2.4: System structures of a C-RAN [1]*

The premier C-RAN configuration is a full centralization structure. This structure known as the stacked BBU structure has significant benefits in terms of operation and maintenance, but incurs a high burden on fronthaul since the functions of the physical layer, the medium access control (MAC) layer and the network layer, i.e., Layer 1, Layer 2, Layer 3, of the conventional BS are moved into the BBU [45]. As a result, the BBU contains all processing and managing functions of the traditional BS and the performance of the C-RAN is clearly constrained by the fronthaul
2.3. Green Cloud Radio Access Networks: A Recent Trend for CoMP

link capacity. With densely deployed RRHs, the fronthaul traffic generated from a receiving terminal with several MHz bandwidth could be easily scaled up to multiple Gb/s. This is because, each of the transmitted RF signals by a receiving terminal need to be sampled and quantized at the RRHs and then forwarded to the BBU pool. Even under moderate mobile traffic, a commercial fiber link with tens of GHz capacity could thus be easily overwhelmed.

The second option is a partial centralization structure. This structure is also called as stand-alone Layer 1 structure, where the RRH integrates the RF functions and some strictly RF-related baseband processing functions. The other functions in the physical layer and the upper layers remain in the BBU. The advantages of this structure are the RRH-BBU overhead and the constraints on fronthaul can be alleviated since the major computational burden of RANs is in the physical layer. However, the disadvantages of this structure are some advanced features such as CoMP transmission and reception, and spatial cooperative processing for distributed massive multiple input multiple output (MIMO) cannot be supported efficiently. In addition, the interaction and connection between physical layer and MAC layer could also be complex and more difficult.

Hybrid centralization is the other option for the C-RAN structure. The partial functions in physical layer such as the user specific or cell specific signal processing functions are removed from BBUs and assembled into a new separated processing unit, which may be a part of the BBU pool. The advantage of the hybrid centralization is its flexibility to support resource sharing and low energy consumption in BBUs.

In this thesis, several advance strategies based on sparse beamforming technique to optimize the performance under a fully centralized structure are proposed as it simplifies the functions and capabilities of the RRHs. For future research, these works can be extended to decentralized structure for huge network cooperation. A good cooperation mechanism design is required to motivate all the C-RANs in a huge decentralized network structure to support the inter-system joint cooperation.
2.4 Downlink Beamforming Design for Green C-RANs.

2.4.1 Beamforming

In the beginning of a traditional cellular system, each BS has no information about the locations of the receiving terminals in its serving area. Thus, the BS simply radiates the dedicated information signals blindly in all directions within the sector cell depending to its pattern. As a result, the dedicated information signals to the intended receiving terminals would interfere to the other receiving terminals within nearby cells, which are working on the same frequency as co-channel cells is implemented. As its spread to areas with no present recipients, energies are wasted.

It is consider as an ideal scenario if the BS had perfect knowledge of the exact locations of the receiving terminals. However this assumption is overly optimistic, with no feasible hardware to make that precision and this configuration is impossible in a practical scenario. Initially, the work that addresses array processing of incoming signals has been reported in [46]. Then, more studies in the area of beamforming has been done for space division purposes in mobile communications [47–60]. The authors in [47] were the first to develop an adaptive beamforming technique.

Beamforming can create different radiation patterns by using antenna arrays and an adaptive algorithm. The variable patterns created by beamforming technique follow from spatial constructive and destructive interference of the signal wavefront in different directions. A pattern changes when the signal feeding the different antenna elements is phased. Generally, such procedure steers the main lobe in the plane where the elements are arranged and eventually the nulls are steered as well. By changing each element’s signal amplitude, a large variety of possible patterns can be achieved [61]. A detailed knowledge about a receiving terminal location is needed to develop a proper formation of the beams. Location detection techniques using electronic scanning with antenna arrays have been developed mainly for military purposes and satellite communications. Lately, this technique has been applied
in cellular networks. Particularly, [62] reports in detail several location detection techniques. The techniques to detect the locations of receiving terminals usually coined as estimation of direction of arrival (DoA) or angle of arrival (AoA). The idea is to find the angle between the receiving terminal-BS line and the antenna boresight. Note that the antenna boresight is the plane perpendicular to the antenna surface. To get the right position, the BS has to respond to the receiving terminal in the same direction where its signal came from as shown in Figure 2.5. Therefore, the direction of departure (DoD) or angle of departure (AoD) denote by $\theta$ has to be the same as the DoA for the specific receiving terminal. AoD is a more common term in the standardisation documents of 3rd Generation Partnership Project (3GPP) [63].

![Antenna elements](image)

**Figure 2.5:** Estimation of direction of arrival (DoA).

The arrays used for BSs are assumed to be equidistant, meaning that the distance between each two adjacent elements is equal to $d$, where $d \leq \lambda/2$. The sidelobes are increasing with the increasing of $d$ and reach a critical point when $d = \lambda/2$. If $d > \lambda/2$, new parasite sidelobes appear, i.e., grating lobes, and the
2.4. Downlink Beamforming Design for Green C-RANs.

result of spatial undersampling of the transmitted signal or the received signal. This phenomenon is an analogous to the aliasing effect that appears when this signal is undersampled. Grating lobes lead to ambiguities in the directions of the departing or arriving signals. This is because parasite copies of these signals replicate themselves in space in unwanted directions.

Channel state information (CSI) is another key component needed in the design of beamformers to acknowledge the BSs about the radio environment features such as path loss, fading and shadowing between the BS and the intended receiving terminal. In a C-RAN system, precoding is done by applying complex weighting to the signal before radiating it in the air as shown in Figure 2.6. The transmitted signal from the $n$-th RRH to the $i$-th receiving terminal, i.e., $x_{n,i} \in \mathbb{C}^{M\times1}$ can be written as

$$x_{n,i} = \sum_{m=1}^{M} w_{n,i,m}s_{n,i,m}, \quad (2.1)$$

where $w_{n,i,m}$ is the $m$-th scalar element in the beamforming vector for the $i$-th receiving terminal from the $n$-th RRH and $s_{n,i,m}$ is the baseband data symbol (on the constellation diagram) intended for modulation and transmission from $m$-th antenna, of the $n$-th RRH, towards the $i$-th receiving terminal.

2.4.2 Linear Antenna Array

Adaptive antenna system (AAS) or smart antennas are collected of at least two antennas working in harmony to create a unique radiation pattern which is performed with hardware or is carried out digitally [64]. Arrays of antennas can be in any geometry form such as linear arrays, circular arrays, planar arrays and conformal arrays. The details about these arrays of antennas can be referred in [65, 66]. This section presents a fundamental concept of a linear antenna array [67].

As illustrated in Figure 2.7, a signal wavefront, $z(t)$, impinging on an antenna array comprising $M$ antennas spaced $d$ apart each other at angle $\theta$, and has a band-
width $B$ can be expressed as

$$z(t) = \beta(t)e^{j2\pi v_c t}. \quad (2.2)$$

In (2.2), $\beta(t)$ is the complex envelope representation of the signal and $v_c$ is the carrier frequency. Furthermore, let denote the traveling time of the wavefront across any two adjacent antennas as $T_z$. It can be stated that

$$T_z = \frac{d \sin(\theta)}{c}, \quad (2.3)$$

where $c$ is the speed of light. It is assumed that the maximum time of the wavefront traveling along one array is to be much smaller than the reciprocal of the bandwidth.
of all transmitted signals, i.e.,

$$B \ll \frac{1}{(M - 1)T_z}.$$  \tag{2.4}$$

By assuming that antenna element patterns are identical, the received signal at the first antenna can be defined as

$$y_1(t) = z(t) = \beta(t)e^{j2\pi \nu c t}$$ \tag{2.5}$$

and the received signal at the second antenna can be defined as

$$y_2(t) = z(t - T_z) = \beta(t - T_z)e^{j2\pi \nu c (t - T_z)}.$$ \tag{2.6}$$

Without loss of generality, under the narrowband assumption in the equation (2.4),

**Figure 2.7:** A schematic of a wavefront impinging across an array of antenna.
2.4. Downlink Beamforming Design for Green C-RANs.

$B \ll 1/T_z$. It is clear that

$$\beta(t - T_z) \approx \beta(t). \quad (2.7)$$

Let denote the wavelength of the signal wavefront as $\lambda_c$ and $\nu_c/c = 1/\lambda_c$, then the received signal at the second antenna can be rewritten as follows

$$y_2(t) = y_1(t) e^{-j2\pi\sin(\theta)\frac{d}{\lambda_c}}. \quad (2.8)$$

Similarly, the received signal at the $k$-th antenna, i.e., $k = 1, 2, \cdots, M$, can be calculated as

$$y_k(t) = y_1(t) e^{-j2\pi(k-1)\sin(\theta)\frac{d}{\lambda_c}}. \quad (2.9)$$

By referring to the equations (2.5), (2.8) and (2.9), it can be concluded that the signals received at any two array elements are identical except for a phase shift which depends on the angle of arrival and the array geometry.

Now, let consider a free field environment where neither scatterers and nor multipath exists. A planar continuous-wave wavefront of frequency $\nu_c$ arriving from an angle $\theta$ will introduce a spatial signature across the antenna array. This spatial signature is a function of AoA, antenna element patterns and antenna array geometry. The complex $M \times 1$ vector called as array response vector is

$$a(\theta) = \left[ a_1(\theta), a_2(\theta), \cdots, a_M(\theta) \right]^T. \quad (2.10)$$

Therefore, for the linear antenna array with identical element patterns, the array response vector can be written as

$$a(\theta) = \begin{bmatrix} 1 \\ e^{-j2\pi\sin(\theta)\frac{d}{\lambda_c}} \\ \vdots \\ e^{-j2\pi(M-1)\sin(\theta)\frac{d}{\lambda_c}} \end{bmatrix}. \quad (2.11)$$

Similarly, the array response vector for a transmit linear antenna array with identical
2.4. Downlink Beamforming Design for Green C-RANs.

Element patterns also can be translated as

$$a(\theta) = \begin{bmatrix} 1 & e^{-j2\pi \sin(\theta) \frac{d}{\lambda_c}} & \ldots & e^{-j2\pi (M-1) \sin(\theta) \frac{d}{\lambda_c}} \end{bmatrix}. \tag{2.12}$$

As a result, the multiple input single output (MISO) channel between the antenna array and a receiving terminal $i$ can be defined as

$$h_i = \xi_i a(\theta_i), \tag{2.13}$$

where $\xi_i$ captures both effects of channel fading, i.e., fast and slow fading, and pathloss. Besides, $\theta_i$ is the AoD of the receiving terminal $i$ with respect to the broadside of the antenna array. Antenna arrays open up a spatial dimension to improve capacities of wireless communication systems due to the fact that smart beam patterns can be shaped by controlling the phases of individual antennas of the array. Interestingly, power-efficient beams can be steered towards intended receiving terminals. Therefore, the interference imposed on unintended receiving terminals can be diminished. Smart beam patterns are performed via algorithms based on certain criteria and can be implemented using hardware or software. However, the latter technique is easier to operate such as using digital signal processing [64]. For instance, these criteria could be either minimising transmit power with constraints on receiving terminals’ signal-to-interference-plus-noise ratios (SINRs) or maximising receiving terminals’ sum rate with constraints on transmit power.

2.4.3 Downlink Beamforming Design for Full Cooperation Multiuser C-RANs

Let consider a green C-RAN system that consists of a BBU pool, N RRHs, each is equipped with $M$ antennas and installed with a renewable energy harvesting device, and $K_i$ single antenna information-receiving terminals (ITs). Furthermore, let $\mathcal{L}_b = \{1, \ldots, N\}$ and $\mathcal{L}_i = \{1, \ldots, K_i\}$, respectively, indicate the set of indexes of the RRHs and the ITs in the green C-RAN system. Let $w_{ni} \in \mathbb{C}^{M \times 1}$ be the beamforming vector formed by the $n$-th RRH towards the $i$-th receiving terminal, $i \in \mathcal{L}_i$. 
2.4. Downlink Beamforming Design for Green C-RANs.

We view all N RRHs of the C-RAN as a single virtual RRH and formulate the problem from the perspective of sparse optimisation. The antennas of the virtual RRH can be partitioned into N groups, each corresponding to an individual RRH. Let \( w_i = [w_{1i}^H, \cdots, w_{Ni}^H]^H \in \mathbb{C}^{MN \times 1} \) indicate the beamforming vector formed by the virtual RRH towards the \( i \)-th receiving terminal. Let \( w_n = [w_{n1}^H, \cdots, w_{nKi}^H]^H \in \mathbb{C}^{MN \times 1} \) denote the beamforming vector formed by the \( n \)-th RRH towards all of the \( K_i \) receiving terminals in the C-RAN system. The requirement that some RRHs may not participate in a transmission towards the \( i \)-th receiving terminal, due to some energy restrictions, translates to the group sparse structure of the virtual beamformer, i.e., \( w_i \). That is, if \( w_{ni} = 0 \), then the \( n \)-th RRH is not participating in serving the \( i \)-th receiving terminal. Similarly, inserting \( w_{ni} = 0 \) in \( w_n \) means that the \( i \)-th receiving terminal is not served by the \( n \)-th RRH, due to shortage of energy budget at the \( n \)-th RRH.

For a full cooperation system configuration, all the beamformers from the RRHs in a C-RAN are participating in serving all the receiving terminals, as illustrated in Figure 2.8. Mathematically, in this configuration, \( w_{ni} \neq 0 \), \( \forall n \in \mathcal{L}_b \), \( \forall i \in \mathcal{L}_i \).

Let \( h_{n,i} \in \mathbb{C}^{M \times 1} \) denote the channel vector between the \( n \)-th RRH and the \( i \)-th receiving terminal. Then, the received signals at the \( i \)-th receiving terminal, \( i \in \mathcal{L}_i \) in a C-RAN downlink network, i.e., \( y_i \in \mathbb{C} \) can be expressed as

\[
y_i = h_i^H w_i s_i + \sum_{j \in \mathcal{L}_i, j \neq i} h_{j}^H w_j s_j + n_i, \tag{2.14}
\]

where \( h_i = [h_{1i}^H, \cdots, h_{Ni}^H]^H \in \mathbb{C}^{MN \times 1} \) denotes the overall channel vector from the virtual RRH to the \( i \)-th receiving terminal, \( s_i \sim \mathbb{C} \mathbb{N}(0, 1) \) is the intended symbol for the \( i \)-th receiving terminal and \( n_i \sim \mathbb{C} \mathbb{N}(0, \sigma_i^2) \) is the zero-mean circularly symmetric complex Gaussian (ZMCSCG) noise. The terms at the right hand side of (2.14), respectively, represent the intended information-carrying signal for the \( i \)-th IT, the inter-user interference caused by all other non-desired information beams, and the additive white Gaussian noise. Note that (2.14) confirms the advantage of the C-
2.4. Downlink Beamforming Design for Green C-RANs.

RAN configuration in terms of ICI mitigation. Thus, this leads to the improvement of throughput of the overall system.

To make sure the quality of service is satisfied at the receiving terminals, SINR must be calculated in the system design. Let $\hat{y}_i = h_i^H w_i s_i$ represents the intended information-carrying signal for the $i$-th IT, then the received useful signal power, $P_i$, $i \in \mathcal{L}_i$ can be expressed as

\[
P_i = \mathbb{E}(\hat{y}_i \hat{y}_i^H) = \mathbb{E}(h_i^H w_i s_i s_i^H w_i^H h_i).
\] (2.15)

In this thesis, $\mathbb{E}(s_i s_i^H) = 1$ is assumed, therefore (2.15) can be reduced to

\[
P_i = h_i^H w_i \mathbb{E}(s_i s_i^H) w_i^H h_i
= h_i^H w_i w_i^H h_i
= |h_i^H w_i|^2
\] (2.16)
2.5. Convex Optimization

Let assume the noise variance, \( \sigma_i^2 \) is identical at all receiving terminals. Then, the SINR at the \( i \)-th IT, \( \text{SINR}_{i}^{[IT]} \), \( i \in \mathcal{L}_i \), can be defined as

\[
\text{SINR}_{i}^{[IT]} = \frac{|h_i^H w_i|^2}{\sum_{j=\mathcal{L}_i, j \neq i} |h_i^H w_j|^2 + \sigma_i^2}.
\]  

(2.17)

2.5 Convex Optimization

Convex optimization has become the most widely researched area in optimization because of its ability in solving very large, practical engineering problems reliably and efficiently. Optimization is a mathematical programming for selecting the best possible element, satisfying the given constraints [68]. The objective of the optimization problem is to minimise or maximise a function. Convex optimization deals with the minimisation of a convex objective function or maximisation of a concave function subjected to convex constraints. Background study of convex optimisation are comprehensively discussed in [68–72] and can be perfectly applied to either engineering field or non-engineering field like communications, signal processing, mechanics, logistics, finance and many others [73].

In telecommunication, some problems can be translated into convex optimization problems. If a problem is in a convex form, then it can provide a globally optimal solution. But most of telecommunication practical problems are non-convex and the hardest part is to transform into a convex form. If the problem cannot be transformed into a convex form, then a simplification procedure can be used and would seek a sub-problem, convergent to a solution of the original problem.

A set \( \mathcal{C} \) is convex if the line segment between any two points in \( \mathcal{C} \) lies in \( \mathcal{C} \). For instance, for any \( x_1, x_2 \in \mathcal{C} \) and \( 0 \leq \theta \leq 1 \), if

\[
\theta x_1 + (1 - \theta)x_2 \in \mathcal{C},
\]  

(2.18)

the set \( \mathcal{C} \) is convex set. In the convex set \( \mathcal{C} \), every point in the set can be seen by every other point, along an unobstructed straight path between them, where unobstructed means lying in the set.
2.5. Convex Optimization

A set \( C \) is called a cone if \( \theta x \in C \), where \( x \in C \) and \( \theta \geq 0 \). Then, for any \( x_1, x_2 \in C \) and \( \theta_1, \theta_2 \geq 0 \), the set \( C \) is a convex cone if

\[
\theta_1 x_1 + \theta_2 x_2 \in C.
\]  

(2.19)

Example of a convex cone is illustrated in Figure 2.9, where points of this form can be described geometrically as forming the two-dimensional pie-slice, with apex 0 and edges passing through \( x_1 \) and \( x_2 \). The pie-slice shows all the points of the form \( \theta_1 x_1 + \theta_2 x_2 \). The apex of the slice that corresponds to \( \theta_1 = \theta_2 = 0 \) is at 0 and its edges pass through the points \( x_1 \) and \( x_2 \).

![Figure 2.9: Example of a convex cone [68].](image)

A function \( f : \mathbb{R}^n \to \mathbb{R} \) is convex if the domain of \( f \) is convex and for all \( x \) and \( y \) that are belong to the domain of \( f \) and for any \( 0 \leq \theta \leq 1 \) as follows

\[
f(\theta x + (1-\theta)y) \leq \theta f(x) + (1-\theta)f(y), \forall \theta \in [0,1].
\]  

(2.20)

If strict inequality holds in (2.20) whenever \( x \neq y \) and \( 0 < \theta < 1 \), the function \( f \) is strictly convex. It can be concluded that a function \( f \) is concave, if \(-f\) is convex,
2.5. Convex Optimization

and strictly concave if \(-f\) is strictly convex. Geometrically, the inequality in (2.20) can be interpreted as a line segment between \((x, f(x))\) and \((y, f(y))\) that lies above the graph of \(f\) as presented in Figure 2.10.

![Figure 2.10: Example of a convex function [68].](image)

The generic standard form of an optimisation problem [68, 73] can be expressed as follows

\[
\min_x f_0(x) \\
s.t. \quad C1 : f_i(x) \leq 0, \quad i = 1, 2, \cdots, m, \\
C2 : h_j(x) = 0, \quad j = 1, 2, \cdots, p, \tag{2.21}
\]

where \(x \in \mathbb{R}^n\) is the optimization variable, \(f_0 : \mathbb{R}^n \to \mathbb{R}\) is the objective function, \(f_i : \mathbb{R}^n \to \mathbb{R}, \quad i = 1, 2, \cdots, m\), are the inequality constraint functions, and \(h_j : \mathbb{R}^n \to \mathbb{R}, \quad j = 1, 2, \cdots, p\), are the equality constraint functions. All \(f_i(x), i = 0, 1, 2, \cdots, m\) have to be convex and all \(h_j(x), j = 0, 1, 2, \cdots, p\) have to be affine functions. The goal of the problem is to find the minimum value of objective function \(f_0(x)\) that satisfies all the requirements of inequality and equality constraints. If \(x^* \in x\) and \(x^*\) minimizes the function \(f_0(x^*)\) over all feasible \(x\), then \(x^*\) is called a feasible solution.
2.5. Convex Optimization

to the optimisation problem. This means that a solution is not just any \( x \) that satisfies the constraints, but the one that has an optimal value amongst all feasible values. Minimizing it is defined as:

\[
x^* = \inf \left\{ f_0(x) | f_i \leq 0, \ i = 1, \ldots, m, \ h_j = 0, \ j = 1, \ldots, p \right\}.
\] (2.22)

If the problem is infeasible then \( x^* = \infty \). If the problem in unbounded from below then \( x^* = -\infty \). On contrary, if the cost function is concave, meaning that the curved is inwards, it can be a subject to maximisation. Similarly, if the inequality constraints are concave functions, then the first constraint, \( C_1 \) in (2.21) becomes \( f_i(x) \geq 0, (i = 1, 2, \ldots, m) \). The equality constraints always have to be affine.

A slack variable is commonly used in convex optimisation transformation technique. Let consider this condition in (2.21), \( f_i \leq 0 \), if and only if \( s_i \geq 0 \), it is sufficient to replace them with the constraint \( f_i + s_i = 0 \). In this example, the presented general form, (2.21) will be transformed into:

\[
\begin{align*}
\min_x & \quad f_0(x) \\
\text{s.t.} & \quad C_1 : f_i(x) + s_i = 0, \ i = 1, 2, \ldots, m, \\
& \quad C_2 : h_j(x) = 0, \ j = 1, 2, \ldots, p, \\
& \quad C_3 : s_i(x) \geq 0, \ i = 1, 2, \ldots, m.
\end{align*}
\] (2.23)

A new variable \( s_i \), called a slack variable is introduced and the original inequality constraint \( f_i(x) \leq 0 \) is replaced by the expression \( f_i(x) + s_i = 0 \). Simply put a slack variable can ease the definitions of a convex problem by replacing each inequality constraint with an equality and a non-negative constraint [68].

In a convex optimization problem, since a local minimum is also the global minimum, the global minimum can be attained by any Gradient Descent or Hill Climbing algorithm [68]. A well researched topic in convex programming is linear programming which is a program with linear objective function and linear/affine constraints. Recently, the developments in convex programming extend the results and algorithms of linear programming to more complicated convex programs, e.g.,
conic programming. A conic programming is a linear programming with generalised inequalities.

Let consider a common class of optimal transmit downlink beamforming for the proposed full cooperation scheme in the green C-RAN as discussed in section 2.4.3. The objective function of this optimization problem is to calculate a set of $w_{ni}, n \in \mathcal{L}_b, i \in \mathcal{L}_i$, that minimizes the total transmit power while guaranteeing SINR requirements, $\gamma_i, i \in \mathcal{L}_i$, of all the ITs in the system, with a given power budget at each RRH, $P_n^{[T_{max}]}$. This optimization problem can be written as

$$\min_{w_{ni}} \sum_{n \in \mathcal{L}_n} \sum_{i \in \mathcal{L}_i} |w_{ni}|^2$$

s.t. $C1 : \sum_{j=\mathcal{L}_i, j \neq i} \frac{|h_i^H w_j|^2}{|h_i^H w_i|^2 + \sigma_i^2} \geq \gamma_i, \forall i \in \mathcal{L}_i,$

$C2 : P_n^{[Tx]} \leq P_n^{[T_{max}]}, \forall n \in \mathcal{L}_n.$

For simplicity, it is assumed that the set of $\gamma_i$ in (2.24) is feasible. Note that this problem has a quadratic form and its can be verified that the SINR constraints in the proposed problem are non-convex.

### 2.6 Semidefinite Programming (SDP)

The non-convex problem in (2.24) can be reformulated by using SDP, where this programming is one of the powerful convex optimization techniques. SDP deals with the minimization of linear functions, subject to linear equalities that contain a linearised matrix term and also subject to non-negative matrix inequalities. The latter implies the use of semidefinite positive matrices. Semidefinite programs encompass a larger number of convex problems, because linear and conic programming problems are subclasses of SDP. Interior point methods described in [68] can be used for solving SDP. Further information about this kind of optimisation is available in [74]. Now, let rewrite (2.24) as follows
2.6. Semidefinite Programming (SDP)

\[
\min_{w_{ni}} \sum_{n \in L_b} \sum_{i \in L_i} w_{ni} w_{ni}^H \tag{2.25}
\]

s.t.
\[
C_1: \frac{h_i^H w_i w_i^H h_i}{\sum_{j \in L_i, j \neq i} h_i^H w_j w_j^H h_i + \sigma_i^2} \geq \gamma_i, \forall i \in L_i,
\]

\[
C_2: \sum_{i \in L_i} w_{ni} w_{ni}^H \leq P_n^{T_{max}}, \quad \forall n \in N.
\]

To further simplify (2.25), beamforming matrices, \(W_{ni}\) and \(W_i\), \(\forall n \in L_b, \forall i \in L_i\) are introduced, where \(W_{ni} = w_{ni} w_{ni}^H, W_{ni} \in \mathbb{C}^{M \times M}\) and \(W_i = w_i w_i^H, W_i \in \mathbb{C}^{MN \times MN}\). It is clear that these beamforming matrices, \(W_{ni}\) and \(W_i\), are positive semidefinite (PSD) and the rank of these matrices are one. Then, the additional constraints \(W_{ni} \succeq 0, W_i \succeq 0\) and \(\text{rank}(W_{ni}) = \text{rank}(W_i) = 1, \forall n \in L_b, \forall i \in L_i\), must be added in the problem (2.25). Therefore, this optimization problem can be rewritten as

\[
\min_{W_{ni}} \sum_{n \in L_b} \sum_{i \in L_i} W_{ni} \tag{2.26}
\]

s.t.
\[
C_1: \frac{h_i^H W_i h_i}{\sum_{j \in L_i, j \neq i} h_i^H W_j h_j + \sigma_i^2} \geq \gamma_i, \forall i \in L_i,
\]

\[
C_2: \sum_{i \in L_i} W_{ni} \leq P_n^{T_{max}}, \quad \forall n \in L_b,
\]

\[
C_3: W_{ni} \succeq 0, \forall n \in L_b, \forall i \in L_i,
\]

\[
C_4: W_i \succeq 0, \forall i \in L_i,
\]

\[
C_5: \text{rank}(W_{ni}) = 1, \forall n \in L_b, \forall i \in L_i,
\]

\[
C_6: \text{rank}(W_i) = 1, \forall i \in L_i.
\]

The constraints C3 and C4 in this optimization problem are to guarantee that \(W_{ni}\) and \(W_i, \forall n \in L_b, \forall i \in L_i\), are positive semidefinite and Hermitian matrix. Then, let consider the following property

\[
x^H A x = \text{tr}(xx^H A) = \text{tr}(A xx^H). \tag{2.27}
\]
From a mathematical point of view, the property in (2.27) can be interpreted as the inner vector product is equal to the trace of the outer product. If \( A = I \), then

\[
x^H x = \text{tr}(xx^H).
\] (2.28)

By adding this property and \( H_i = h_i h_i^H, H_i \in \mathbb{C}^{MN \times MN} \) into the optimization problem, the constraint C1 can be reformulated as

\[
C1 : \text{tr}(H_i W_i) \geq \gamma_i \left( \sum_{j=\mathcal{L}_i, j \neq i} \text{tr}(H_j W_j) + \sigma_i^2 \right), \forall i \in \mathcal{L}_i,
\]

\[
C1 : \gamma_i^{-1} \text{tr}(W_i H_i) - \sum_{j=\mathcal{L}_i, j \neq i} \text{tr}(H_j W_j) - \sigma_i^2 \geq 0, \forall i \in \mathcal{L}_i.
\] (2.29)

In sequel, the optimization problem (2.26) can be expressed as

\[
\min_{W_{ni}} \sum_{n \in \mathcal{L}_b} \sum_{i \in \mathcal{L}_i} \text{tr}(W_{ni})
\]

s.t.

\[
C1 : \gamma_i^{-1} \text{tr}(W_i H_i) - \sum_{j=\mathcal{L}_i, j \neq i} \text{tr}(H_j W_j) - \sigma_i^2 \geq 0, \forall i \in \mathcal{L}_i,
\]

\[
C2 : \sum_{i \in \mathcal{L}_i} \text{tr}(W_{ni}) \leq P_n^{\text{Tmax}}, \forall n \in \mathcal{L}_b,
\]

\[
C3 : W_{ni} \succeq 0, \forall n \in \mathcal{L}_b, \forall i \in \mathcal{L}_i,
\]

\[
C4 : W_i \succeq 0, \forall i \in \mathcal{L}_i,
\]

\[
C5 : \text{rank}(W_{ni}) = 1, \forall n \in \mathcal{L}_b, \forall i \in \mathcal{L}_i,
\]

\[
C6 : \text{rank}(W_i) = 1, \forall i \in \mathcal{L}_i.
\]

Note that the rank-one constraints of rank\((W_{ni}) = 1\) and rank\((W_i) = 1\) can be relaxed via semidefinite relaxation (SDR) approach. Dropping the last two constraints
2.7 Sparse Beamforming Design for C-RAN with SWIPT Systems

in (2.30), results in a SDP form as follows

$$\begin{align*}
\min_{\mathbf{W}_n} & \quad \sum_{n \in \mathcal{L}_b} \sum_{i \in \mathcal{L}_i} \text{tr}(\mathbf{W}_{ni}) \\
\text{s.t.} & \quad C1 : \gamma_i^{-1} \text{tr}(\mathbf{H}_i \mathbf{W}_i) - \sum_{j \neq i} \text{tr}(\mathbf{H}_i \mathbf{W}_j) - \sigma_i^2 \geq 0, \quad \forall i \in \mathcal{L}_i, \\
& \quad C2 : \sum_{i \in \mathcal{L}_i} \text{tr}(\mathbf{W}_{ni}) \leq P_{n}^{\text{Tmax}}, \quad \forall n \in \mathcal{L}_b, \\
& \quad C3 : \mathbf{W}_{ni} \succeq 0, \quad \forall n \in \mathcal{L}_b, \forall i \in \mathcal{L}_i, \\
& \quad C4 : \mathbf{W}_i \succeq 0, \quad \forall i \in \mathcal{L}_i,
\end{align*}$$

(2.31)

Dropping these rank one constraints not only enlarges the feasible set of the problem (2.30) but also leads to a relaxed SDP problem. This relaxation is referred to SDR technique. For general non-convex quadratic problems, solving an SDR problem usually gives an optimal solution with rank of larger than one. In such cases, SDR can only provide a lower bound on the optimal objective function and possibly attain an approximate solution to the original problem [75]. When using SDR results in $\mathbf{W}_{ni}$ and $\mathbf{W}_i$, $\forall n \in \mathcal{L}_b, \forall i \in \mathcal{L}_i$, solutions with ranks higher than one, a randomization procedure can be used to find approximate rank-one solutions. This randomization procedure can be referred in [76–78].

Since (2.24) has a specific structure that it can be turned into a convex form, strong duality holds for (2.24). Furthermore, it can be shown that the SDR form of (2.30) which is (2.31), is the Lagrangian dual of (2.24) [75]. Therefore, (2.31) is exactly equivalent to the original problem (2.24). This fact has been confirmed in [79]. It can be proved that the solution to (2.31) always admits rank-one matrices $\mathbf{W}_{ni}$ and $\mathbf{W}_i$, $\forall n \in \mathcal{L}_b, \forall i \in \mathcal{L}_i$, which directly yields the solution to (2.24) using $\mathbf{W}_{ni} = w_{ni}w_{ni}^H$ and $\mathbf{W}_i = w_iw_i^H$.

2.7 Sparse Beamforming Design for C-RAN with SWIPT Systems

The integration of CoMP networks and energy harvesting technique, where the signals transmitted from RRHs can be exploited by the energy receiving terminals
(ETs) for self-sustainability, has attracted the attention of researchers. The concept of simultaneous wireless information and power transfer (SWIPT) has been introduced in wireless communication systems to enable energy self-sustainability for the battery limited portable devices. A typical SWIPT system with separate ITs and ETs is shown in Figure 2.11.

Figure 2.11: A SWIPT system with separate information and energy receiving terminals.

Numerous research has been conducted in SWIPT. In [80], the authors investigate a three-node robust SWIPT with multiple input single output (MISO) configuration. The authors in [81] extend the previous work to multiuser scenarios with the assumption of perfect CSI. Moreover, since no information is carried by the energy-carrying signals towards the ETs [81], artificial noise generated at the individual RRHs can be used to prevent the ETs from eavesdropping and the physical-layer secrecy is then improved [82, 83].

CoMP transmission that allows neighbouring base stations to collaborate with each other for SWIPT has been extensively scrutinised as a highly promising solu-
2.7. Sparse Beamforming Design for C-RAN with SWIPT Systems

It has been proven that the total transmit power in a CoMP transmission is reduced when a full cooperation is enabled [21]. However, if all the RRHs in a C-RAN cooperate to transfer energy to all ETs and share the information of all ITs, huge fronthaul capacity is needed [8]. In practice, all the RRHs in a C-RAN are connected with a cloud computing centralized unit via rate-limited fronthaul links. Therefore, full cooperation may be infeasible.

All the aforementioned solutions have sparked interest among telecommunication researchers to investigate multi-cell cooperation transmission with restricted fronthaul capacity [11–14, 18, 85–91] motivated by the remarkable performance of reweighted \( \ell_1 \)-norm minimisation algorithm in compressing sensing introduced in [9]. These studies proposed an iterative sparse beamforming algorithm to lessen the load of the fronthaul links and used \( \ell_1 \)-norm of the beamforming vector to approximate the cluster size. Interestingly, [13] adopted a new weight factor updating rule and achieved a better tradeoff between the total power transmit from all BSs and the sum fronthaul capacity.

However, most of the sparse beamforming literatures cited above do not consider the existence of energy harvesting devices and renewable energy productions for the green network. In [10], the resource allocation algorithm design for a CoMP-SWIPT network is proposed by optimising the transmit beamforming vectors at the CP and energy sharing between the CP and RRHs. This architecture however, does not consider renewable energy resources that can be further extended for energy cooperation and energy trading in the C-RAN with SWIPT network.

The data circulation between the CP and the RRHs for full coordination requires huge fronthaul signalling overhead, which may be infeasible in practice. Therefore, motivated by reweighted \( \ell_1 \)-norm convex relaxation in compressive sensing, the authors in [10, 13] proposed dynamic iterative sparse beamforming designs with QoS constraints for capacity-limited fronthaul links in CoMP systems.

Clustering techniques can reduce the estimation overhead and computational complexity significantly by limiting the number of RRHs in one cluster, and thereby, resulting to low capacity requirements on the fronthaul. However, these techniques
Sparse Beamforming Design for C-RAN with SWIPT Systems

have drawbacks where the C-RAN large-scale cooperative processing gains and capacity will be reduced. Through these approaches, the centralized processing capability will not be optimized. Disjoint clustering and user-centric clustering are the two classical types of RRH clustering schemes. In disjoint clustering architecture, the C-RAN is categorized into non-overlapping clusters, and RRHs in each cluster jointly serve all receiving terminals within the coverage area. On contrary, receiving terminals at the cluster edge suffer from considerable inter-cluster interference despite its effectiveness in combating the ICI. In user-centric clustering, each receiving terminal is served by an individually selected subset of neighboring RRHs and different clusters for different receiving terminals may overlap. The advantage of this scheme is there is no explicit cluster edge. Such scheme can be further extended to two distinct implementations which relies heavily on the conditions of RRH clustering, dynamic or static over different time slots. In dynamic user-centric clustering, the RRH cluster for each receiving terminal can change over time, allowing for more freedom to fully utilize the fronthaul resources. However, dynamic user-centric clustering also requires a large amount of signalling overhead as new receiving terminal associations need to be established continuously. Meanwhile, in the static user-centric clustering, the receiving terminal association is fixed over time and may only need to be updated as the receiving terminal location changes. Dynamic clustering can outperform significantly the disjoint clustering strategy, while heuristic static clustering schemes can achieve a substantial portion of the performance gain.

The cluster size has been identified as one of the most critical design parameters for clustering scheme. Optimizing the dimension of cluster size can be made possible through the following:

1. The cluster size determines the number of active RRHs at any time. This leads to the density of active RRHs that controls the co-channel interference coming from a scheduled receiving terminal.

2. The number of simultaneously schedules receiving terminals per unit area is determined by the radius of the cluster.
3. The dimensions of a cluster determine the number of RRHs serving a scheduled receiving terminal, leading to the diversity gain experienced due to spatially distributed RRHs.

The derivative of viable successful access probability (SAP) has been made by applying stochastic geometry in [92]. In this work, the clustering of RRHs is formulated as a coalitional game where a merge and split technique has been proposed as an efficient solution through the theoretical result, in which represents a utility function.

Look at different prospective and idea, the clustering of RRHs in this thesis is optimized by using convex optimization technique because of its ability in solving practical engineering problems reliably and efficiently. The strategies proposed in this thesis are based on dynamic RRH-centric clustering, where the RRH cluster for each receiving terminal is changed intelligently depending on the production of renewable energy harvesters installed at each RRH, i.e., power budget. The size of the RRH cluster is changed dynamically depending on its power budget with the aim to minimize the total cost of the network operator as well as to address all the given constraints.

2.8 Resource Management and Energy Trading with the Smart Grid

Equipping the RRHs with renewable energy harvesting devices that can generate local renewable energy from environmental sources, e.g., solar and wind, green communications provide new perspective in reducing energy cost of cellular networks. In practice, renewable energy generation is uneven due to the different efficiencies of renewable energy harvesters and various RRHs installation sites. Therefore, the power from the reliable source, i.e., power grid, is still needed to provide continuous energy supply to all the RRHs in the C-RAN. Power supply from the smart grid is always reliable but expensive because of time-varying energy prices.

Hybrid energy supply from both renewable energy devices and advanced smart grid technology motivates a new idea of energy cooperation and energy trading in
cellular networks as illustrated in Figure 2.12. Unlike traditional one way energy flow from the grid to receiving terminals, smart grid deploys smart meters to enable both two-way energy and information flows [93–96]. The network can maximally benefit from utilizing their local generated renewable energy, purchasing deficit energy from the grid and selling the excessive energy to the grid to make profit [5–7, 18, 21].

![Diagram of two-way communication and energy cooperation with the smart power grid.](image)

**Figure 2.12:** Two-way communication and energy cooperation with the smart power grid.

Let consider a general energy supply and demand model for the green C-RAN. It is assumed that at least one renewable energy harvester, e.g., wind turbine and/or solar panel, is installed at each RRH in order to generate renewable energy from environmental sources, e.g., solar and wind. Furthermore, no RRH is equipped with frequently rechargeable storage devices and the RRHs are obliged to sell the excess power to the grid. At the beginning of the thesis, only a particular time slot is used, thus the time index of variables is ignored for the notational convenience.
Let $E_n$, $B_n$ and $S_n$ denote the amount of renewable energy generated at the $n$-th RRH, the amount of energy needed to be purchased from the grid by the $n$-th RRH and the amount of excessive energy sold to the grid by the $n$-th RRH, respectively. Furthermore, let $P_n^{[\text{Tx}]}$ and $P_n^{[\text{circuit}]}$ indicate the total transmit power at the $n$-th RRH and the hardware circuit power consumption at the $n$-th RRH, respectively. Then, the total energy consumption at the $n$-th RRH, i.e., $P_n^{[\text{total}]}$, is upper-bounded by the total available energy at the $n$-th RRH as follows

$$P_n^{[\text{total}]} = P_n^{[\text{Tx}]} + P_n^{[\text{circuit}]} \leq E_n + B_n - S_n. \quad (2.32)$$

In practice, the price of generating per unit renewable energy $\pi^{[\text{renew}]}$ is much cheaper than the price of purchasing per unit energy from the grid $\pi^{[\text{buy}]}$. From the supply and demand perspective, the RRH purchases additional energy from the grid at a higher price $\pi^{[\text{buy}]}$ and sells the unconsumed energy to the grid at a reduced price $\pi^{[\text{sell}]}$. Intelligibly, $\pi^{[\text{buy}]} \geq \pi^{[\text{sell}]} \geq \pi^{[\text{renew}]}$ holds to avoid the trivial case where any RRH in the cooperative network can make a profit by reselling the purchased energy back to the grid or other RRHs. Note that, in this cooperative network, the total energy purchased from the power grid by all the RRHs is the total renewable energy deficit in the network. Thus, all the RRHs in the C-RAN can maximally benefit from utilizing their local generated renewable energy to provide a green network. As a result, the total energy cost of the cooperative RRHs, denoted by $B^{[\text{total}]}$, can be calculated as

$$B^{[\text{total}]} = \pi^{[\text{renew}]} \sum_{n \in \mathcal{L}_b} E_n + \pi^{[\text{buy}]} \sum_{n \in \mathcal{L}_b} B_n - \pi^{[\text{sell}]} \sum_{n \in \mathcal{L}_b} S_n, \quad (2.33)$$

It is necessary to jointly optimize the resource allocation and energy trading to guarantee the profit of the network operator and also to support green communication. To further reduce the total energy cost, a system should be embedded with the intelligent algorithms to observe, learn and predict the energy that should be purchased from the grid.
2.9 Related Works

Provided that all of the BSs are equipped with renewable energy harvesters and implemented with two-way energy trading, [7, 21] propose a joint energy trading and full cooperation scheme in CoMP network, where the data of all of the users is available at the CP and will be distributed to all of the BSs in the cluster for cooperative transmission via fronthaul links. However, the data circulation between the CP and the BSs requires huge fronthaul signalling overhead when full coordination is enabled. The scheme, nevertheless, takes no account of fronthaul capacity restrictions, which may be infeasible for practical capacity-constrained fronthaul links [8]. Consequently, CoMP with finite fronthaul capacity has been investigated by the scientific community and sparse beamforming technique for partial cooperation is considered as a viable solution to this issue. Motivated by the literature that sparse beamforming problem is commonly formulated as a $\ell_0$-norm optimization problem and handled with reweighted $\ell_1$-norm method in the field of compressive sensing [9], the authors in [11–14, 89] propose dynamic sparse beamforming designs subject to QoS constraints for capacity-limited fronthaul links in CoMP networks. The authors in [10] integrate the aforementioned works with SWIPT concept and study the resource allocation algorithm, under QoS constraints for information receivers and power constraints at the BSs and the CP. It can be perceived that sparse beamforming technique in joint cooperative real-time resource management and energy trading problem in green C-RAN is firstly tackled in [18].

According to the theory of probability, a multi-armed bandit (MAB) is a problem in which a gambler at a row of slot machines has to make a decision on which order and how many times the levers should be pulled to maximize the accumulated reward, also known as linear or classic MAB [17]. In statistics and reinforcement learning, the problem based on MAB concept has been well studied in the literature [16, 97–100]. The research on stochastic MAB problem which is introduced in [101] presents that under certain conditions on reward distributions, a tight asymptotic regret of $\mathcal{O}(\log n)$ can be obtained, where $n$ is the number of rounds played. Note that, regret is the metric for measuring the effectiveness of an MAB
2.9. Related Works

Regret can be calculated as the difference in the total expected reward between always playing the optimal arm and playing arms according to the algorithm [16]. Then, [102] shows that $O(\log n)$ regret can be achieved uniformly over time rather than only asymptotically in the other work [103]. The problem can be categorized as a combinatorial MAB (CMAB) problem if multiple arms are pulled simultaneously and the individual reward for each arm is observed [16]. The CMAB problem has been studied intensively in [104–107].

However, none of this work applies the concept of CMAB in the real-time resource management and energy trading between the C-RAN and the smart grid. To employ an abstract idea of MAB for the CP to learn from the behaviour of the energy trading in C-RAN iteratively, let consider each arm corresponds to the size of an energy package to be purchased by the network operator from the day-ahead market prior to the actual time of energy demand. Therefore, the new responsibility of the CP is to find the set of optimal sizes of the energy packages to be purchased from the day-ahead market without the initial knowledge of forthcoming instantaneous energy demand, in order to minimize the total energy cost of the network operator. At each time instant, the CP learns from behaviour of cooperative energy trading and predicts an amount of energy consumed by the individual RRH to further minimize the amount of energy that should be purchased from the real-time market, under the a set of constraints.

The other potential concept that can be applied in the real-time resource management and energy trading between the C-RAN and the smart grid is a game theoretical approach. Game theoretical approach is the study of optimal decision making under competition when the decisions of one player in a team will effect the outcome of a situation for all other players involved [94]. On the contrary, the MAB problem models a slot machine attempts to maximize the accumulated reward by iteratively optimizing the decisions among a set of arms based on existing knowledge, known as exploitation, while simultaneously acquiring new knowledge by observing the associated reward, known as exploration [17]. The MAB approach can be jointly implemented with game theoretical approach to further motivate the
potential RRHs with extra energy to assist in neighbourhood energy sharing and trading. A practical energy and communication cooperation mechanism needs to be designed for RRHs by the game theoretical approach. For example, the RRHs could be selfish and prefer to store the harvested energy rather than to cooperate with the other RRHs. In this situation, that particular RRHs need to be offered some extra incentive to encourage them to be good players in a game. A good cooperation mechanism design is required to motivate all the players in a system. This work also can be extended to a huge network cooperation to support the inter-system joint cooperation to a win-win situation for all the systems involved. This work is an interesting direction for future research.

2.10 Concluding Remarks

This chapter begins with brief reviews on a C-RAN powered by renewable energy technologies and a downlink beamforming design. Then, an optimization problem for a downlink beamforming to calculate transmit beamformers for multiple receiving terminals in C-RAN with a constraint of power budget at each RRHs scenario is introduced. A method to transform the non-convex optimization problem into convex optimization problem using semidefinite programming forms is presented, which can be effectively solved by available optimization packets. This chapter also provides an overview on a resource management and energy trading approach for energy cost saving in C-RAN powered by renewable energy sources and smart grid. The two-way energy cooperation between the smart grid and the RRHs in a C-RAN is expected to reshape the non-uniform energy supplies and energy demands over the C-RAN for cost-saving. Hopefully, the technical background provided in this chapter delivers the readers with the basic knowledge of the work areas to have better understanding on the proposed problems in the forthcoming chapters.
Chapter 3

Real-Time Energy Management in Green C-RAN

3.1 Introduction

With enormously increasing demand for mobile data and high data rates, the aggregated power requirements by receiving terminals may exceed the amount of power budget at the remote radio heads (RRHs). Hence, the network operator has to purchase additional energy from the real-time market, i.e., the grid, and may take a risk of losing the profit. To address the aforementioned issue, this chapter introduces the real-time energy management for green cloud radio access networks (C-RANs) using the local renewable energy generation at RRHs.

This chapter proposes three different cooperative real-time energy trading strategies, namely, power-shortage management by partial cooperation, power-shortage management by full cooperation, and overall network energy management by full cooperation, to jointly minimize the energy consumption and the real-time energy trading under the constraints of demand and supply power balancing at RRHs and quality of service satisfaction at user terminals.

For the first strategy, a sparse beamforming problem is formulated as an $\ell_0$-norm optimization problem and solve it using semidefinite relaxation (SDR) and iterative reweighted $\ell_1$-norm approximation of $\ell_0$-norm. The second and the third strategies are formulated as numerically tractable optimization problems and solve...
them using the SDR approach.

3.1.1 Organization

The remainder of this chapter is organized as follows. Section 3.2 presents the system model. In section 3.3, 3.4 and 3.5, the formulations of Strategy 1: Power-Shortage Management by Partial Cooperation, Strategy 2: Power-Shortage Management by Full Cooperation and Strategy 3: Overall Network Energy Management by Full Cooperation, respectively, for cooperative real-time energy trading are introduced. The resulting non-convex problems for all the proposed strategies are reformulated and then transformed into tractable forms using convex relaxation. Numerical simulation results are analyzed in section 3.6. Finally, section 3.7 summarizes the chapter.

3.2 System Model

This model considers a C-RAN with $N$ RRHs, $K_i$ single-antenna information receiving terminals (ITs) and a centralized cloud computing processor (CP). Let $\mathcal{L}_b = \{1, \cdots, N\}$ and $\mathcal{L}_i = \{1, \cdots, K_i\}$ denote, respectively, the set of indexes for the RRHs and the ITs. The CP is the core processing unit in the system that designs and broadcasts all the coordination strategies to the RRHs based on the perfect knowledge of channel state information. The CP has also access to all the data for the ITs and distributes them to all the RRHs for cooperative transmission of information to the individual ITs. Each RRH is equipped with an array of $M$ antenna elements. Here, the energy transmission between the CP and RRHs in the system is assumed to be accomplished via dedicated power lines.

3.2.1 Energy Management Model

From the perspective of capital expenditure (CAPEX) and operating expense (OPEX), at least one renewable energy harvesting device, e.g., wind turbine and/or solar panel, is assumed to be installed at the individual RRHs in order to generate local renewable energy from environmental sources. Whereas, no RRH is equipped with frequently rechargeable storage devices and the RRHs are obliged to transmit the excessive power back to the CP for sale. In practice, the renewable energy gener-
3.2. System Model

vation is unequal due to efficiency of different types of renewable energy harvesting devices and various RRHs locations. Let \( E_n, B_n^{\text{ahead}}, B_n^{\text{real}}, S_n \) be defined, respectively, as the amount of renewable energy generated at the \( n \)-th RRH, the amount of energy that has been purchased from the day-ahead market for the \( n \)-th RRH, the amount of energy that is necessary to be purchased from the real-time market for the \( n \)-th RRH, and the amount of excessive energy sold back to the grid by the \( n \)-th RRH. Furthermore, let \( P_n^{\text{Tx}} \) and \( P_n^{\text{circuit}} \) indicate the total transmit power at the \( n \)-th RRH and the non-transmission hardware circuit power consumption at the \( n \)-th RRH, respectively. Then, the total energy consumption at the \( n \)-th RRH, i.e., \( P_n^{\text{total}} \), is upper-bounded by the total available energy at the \( n \)-th RRH, i.e.,

\[
P_n^{\text{total}} = P_n^{\text{Tx}} + P_n^{\text{circuit}} \leq E_n + B_n^{\text{ahead}} + B_n^{\text{real}} - S_n. \tag{3.1}
\]

In practice, the price of generating per unit renewable energy, denoted by \( \pi^{\text{renew}} \), is much cheaper than the price of purchasing per unit energy from the day-ahead market, represented by \( \pi^{\text{ahead}} \). From the supply and demand’s perspective, it is assumed that the RRH purchases additional energy from the real-time market at a higher price \( \pi^{\text{real}} \) and sells the unconsumed energy back to the grid at a reduced price \( \pi^{\text{sell}} \), i.e., \( \pi^{\text{real}} \geq \pi^{\text{ahead}} \geq \pi^{\text{sell}} \geq \pi^{\text{renew}} \). Consequently, the total energy cost of all the RRHs in the green C-RAN, denoted by \( B^{\text{total}} \), is given by

\[
B^{\text{total}} = \pi^{\text{ahead}} \sum_{n \in \mathcal{L}_b} B_n^{\text{ahead}} + \pi^{\text{real}} \sum_{n \in \mathcal{L}_b} B_n^{\text{real}} + \pi^{\text{renew}} \sum_{n \in \mathcal{L}_b} E_n - \pi^{\text{sell}} \sum_{n \in \mathcal{L}_b} S_n. \tag{3.2}
\]

Thus, it is necessary to jointly optimize the resource allocation and energy trading to guarantee the profit of the network operator.

3.2.2 Downlink Transmission Model

Let denote the aggregate beamformer from all RRHs towards the \( k \)-th IT as \( \mathbf{w}_k = [\mathbf{w}^H_{1k}, \ldots, \mathbf{w}^H_{N_k}]^H \in \mathbb{C}^{MN \times 1} \), where \( \mathbf{w}_{nk} \in \mathbb{C}^{M \times 1} \) is the beamforming vector from the \( n \)-th RRH to the \( k \)-th IT, \( k \in \mathcal{L}_i \). Similarly, the aggregate channel between all RRHs
and the $k$-th IT is denoted as $\mathbf{h}_k = [h_{1k}^H, \cdots, h_{Nk}^H]^H \in \mathbb{C}^{MN \times 1}$, where $h_{nk} \in \mathbb{C}^{M \times 1}$ is the channel vector between the $n$-th RRH and the $k$-th IT, $k \in \mathcal{L}_i$. The received signal at the $k$-th IT, $k \in \mathcal{L}_i$ is given by

$$z_k = \mathbf{h}_k^H \mathbf{w}_ks_k + \sum_{j \neq k} \mathbf{h}_j^H \mathbf{w}_js_j + n_k, \quad \forall k \in \mathcal{L}_i$$

(3.3)

where $s_k$ indicates the data symbol for the $k$-th IT and $n_k \sim \mathcal{C}\mathcal{N}(0, \sigma_k^2)$ is the additive white Gaussian noise at the $k$-th IT. Without loss of generality, it is assumed that the noise variance $\sigma_k^2$ is identical at all ITs and $\mathbb{E}(|s_k|^2) = 1$, $\forall k \in \mathcal{L}_i$. Then, the signal-to-interference-plus-noise ratio (SINR) at the $k$-th IT can be expressed as

$$\text{SINR}_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \neq k} |\mathbf{h}_j^H \mathbf{w}_j|^2 + \sigma_k^2}, \quad \forall k \in \mathcal{L}_i.$$ 

(3.4)

The shortage of power budget occurs when the aggregate available power at a RRH is insufficient to satisfy the demand of multiple ITs. As a result, it is necessary for the network operator to purchase the additional energy from the real-time market at a higher price, which, consequently, may increase the total cost of the network operator. Let $\mathcal{Z} = \{1, \cdots, Z\}$, where $\mathcal{Z} \subset \mathcal{L}_b$, indicate the set of indexes for the RRHs that are in the shortage of power. Let say that the $z$-th RRH is in the shortage of power, if its power budget denoted by $P_{\text{budget}}^z$ is upper-bounded as

$$P_{\text{budget}}^z \leq \frac{\sum_{n \in \mathcal{L}_b} \left( E_n + B_{\text{ahead}}^n - P_{\text{circuit}}^n \right)}{N}, \quad \forall z \in \mathcal{Z}.$$ 

(3.5)

In addition, let assume that the CP is frequently updated with the information of all the RRHs’ power budgets, so that the indexes of RRHs that are in shortage of power budget can be calculated in accordance with (3.5). Subsequently, the optimal user cluster to be served by the RRHs with shortage of power budget, is determined by the CP through evaluation of actual situations, e.g., the location of ITs, the associated channel conditions and power budgets of the RRHs. In this thesis, information of all the RRHs’ power budget are reliable. On the contrary,
if the information of all the RRHs’ power budget are not available at the CP, then a backup solution must be provided. For instance, the CP can simply estimate the current power budget at each of the RRHs by using the previous data or any intelligent software can be used to estimate these information. In the sequel, three different cooperative energy trading strategies are presented to jointly minimize the energy consumption and the real-time energy trading, so that the overall energy cost is reduced.

3.3 Strategy 1: Power-Shortage Management by Partial Cooperation

3.3.1 Problem Formulation

Figure 3.1: Power-shortage management by partial cooperation in the green C-RAN.
3.3. Strategy 1: Power-Shortage Management by Partial Cooperation

As presented in Figure 3.1, a sparse beamforming technique is used to design partial cooperation in the C-RAN to reduce the total energy cost of the network operator by minimizing a linear combination of the fronthaul link capacity consumption of the RRHs with shortage of power budget, denoted by $C_{z}^\text{fronthaul}$, and the maximum power purchased from the real-time market, under the constraint of maintaining the required quality of service (QoS) by the ITs. $C_{z}^\text{fronthaul}$ is formulated as

$$C_{z}^\text{fronthaul} = \sum_{k \in \mathcal{L}_i} ||||w_{zk}||^2_2|| \alpha R_k, \forall z \in \mathcal{Z},$$

where $R_k = \log_2(1 + \gamma_k)$ is the rate in bit/s/Hz and $\gamma_k$ is the corresponding SINR requirement by the $k$-th IT. Note that $||||w_{zk}||^2_2||_0$ is an indicator function that illustrates the scheduling choices of the individual ITs and $w_{zk} = 0$ indicates that the $z$-th RRH is not participating in the joint transmission to the $k$-th IT, due to power restrictions. Under such circumstance, the CP enables the partial cooperation by not delivering data for the $k$-th IT to the $z$-th RRH via the corresponding fronthaul link. Then, the Strategy 1 can be formulated as

$$\min_{w_k, B_n^\text{real}} \alpha \sum_{z \in \mathcal{Z}} C_{z}^\text{fronthaul} + \max_{n \in \mathcal{L}_b} \left\{ B_n^\text{real} \right\}$$

subject to

$$C1 : \text{SINR}_k \geq \gamma_k, \quad \forall k \in \mathcal{L}_i,$$

$$C2 : \sum_{k \in \mathcal{L}_i} ||||w_{nk}||^2_2|| \alpha R_k, \forall z \in \mathcal{Z},$$

$$C3 : P_n^\text{Tx} + P_n^\text{circuit} \leq E_n + B_n^{\text{ahead}} + B_n^{\text{real}} - S_n, \quad \forall n \in \mathcal{L}_b,$$

$$C4 : \sum_{n \in \mathcal{L}_b} B_n^{\text{ahead}} + \sum_{n \in \mathcal{L}_b} B_n^{\text{real}} \leq P_{\text{CP}}^{\text{max}} - P_{\text{CP}}^{\text{circuit}}, \quad \forall n \in \mathcal{L}_b,$$

$$C5 : B_n^{\text{real}} \geq 0, \quad \forall n \in \mathcal{L}_b,$$

$$C6 : S_n \geq 0, \quad \forall n \in \mathcal{L}_b,$$

where $\alpha \geq 0$ can be regarded as the power cost for delivering information from the CP to the RRHs via fronthaul links. $C1$ denotes a set of QoS constraints for $K_i$ ITs. $C2$ indicates that the total transmit power of each RRH, i.e., $P_n^\text{Tx} = \sum_{k \in \mathcal{L}_i} ||||w_{nk}||^2_2||, n \in \mathcal{L}_b$, is constrained by the total available power $P_n^{\text{total}}$ and the hardware circuit power consumption $P_n^{\text{circuit}}$ at the respective RRH, in accordance with (3.1). $C3$ repre-
sents that the total transmit power should not exceed the maximum transmit power allowance, denoted by $P_n^{[\text{Tmax}]}$, at the $n$-th RRH. C4 specifies the constraint for the total power supplied by the CP to the RRHs, where $P_{\text{CP}}^{[\text{circuit}]}$ and $P_{\text{CP}}^{[\text{max}]}$ are the hardware circuit power consumption at the CP and the maximum power provision at the CP, respectively. C5 and C6 are the non-negative constraints set for the optimization variables.

### 3.3.2 Convex Relaxation

The optimization problem in (3.6) is non-deterministic polynomial-time (NP)-hard due to the non-convexity of the constraints C1 and the $\ell_0$-norm representation of the RRHs-ITs scheduling choices in objective function. In accordance with [13], the $\ell_0$-norm representation in problem (3.6) can be transformed into a sum weighted capacity consumption via the reweighted $\ell_1$-norm method.

The fronthaul capacity consumption $C_z^{[\text{fronthaul}]}$ for link between the CP and the $z$-th RRH that is in power budget shortage, can be approximated as follows.

$$C_z^{[\text{fronthaul}]} = \sum_{k \in L_i} \left( || ||w_{zk}||^2 0 \right) \| R_k \right)$$

$$\approx \sum_{k \in L_i} \left( \xi_{zk} ||w_{zk}||^2 1 \right) R_k$$

$$= \sum_{k \in L_i} \xi_{zk} ||w_{zk}||^2 R_k,$$

where $\xi_{zk} \geq 0$ is the weight factor associated with the $z$-th RRH and the $k$-th IT. Let define a block diagonal matrix $D_n \succeq 0$, as

$$D_n \triangleq \text{diag} \left( \begin{array}{c|c} (n-1)M & M \\ \hline 0,...,0,1,...,1,0,...,0 \\ \end{array} \right), \forall n \in L_b. \right)$$

Then, the total transmit power $P_n^{[\text{Tx}]}$ at the $n$-th RRH, can be expressed as

$$P_n^{[\text{Tx}]} = \sum_{k \in L_i} ||w_{nk}||^2 = \sum_{k \in L_i} w_k^H D_n w_k, \quad \forall n \in L_b. \right)$$

Substituting (3.7) and (3.9) into (3.6) and defining $W_k = w_k w_k^H$ and $H_k = h_k h_k^H$. 

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**References:**

the original optimization problem can be formulated as a semidefinite programming (SDP) problem. Then, by applying the SDR approach to relax the rank-one constraints of \( \text{rank}(W_k) \leq 1 \), the problem in (3.6) can be reformulated as

\[
\min_{W_k, \chi} \quad \alpha \sum_{z \in Z} \sum_{k \in L} \xi_{zk} \text{tr}(W_k D_z) R_k + \chi,
\]

s.t. \( C1 : \gamma_k^{-1} \text{tr}(H_k W_k) \geq \sum_{j \neq k} \text{tr}(H_k W_j) + \sigma_k^2, \forall k \in L_i, \)

\( C2 : \sum_{k \in L_i} \text{tr}(W_k D_n) \leq E_n + B_n^{[\text{ahead}]} + B_n^{[\text{real}]} - S_n - P_n^{[\text{circuit}]}, \forall n \in L_b, \)

\( C3 : \sum_{k \in L_i} \text{tr}(W_k D_n) \leq P_n^{[\text{Tmax}]}, \forall n \in L_b, \)

\( C4 : \sum_{n \in L_b} B_n^{[\text{ahead}]} + \sum_{n \in L_b} B_n^{[\text{real}]} \leq P_{\text{CP}}^{[\text{max}]} - P_{\text{CP}}^{[\text{circuit}]}, \)

\( C5 : B_n^{[\text{real}]} \geq 0, \forall n \in L_b, \)

\( C6 : S_n \geq 0, \forall n \in L_b, \)

\( C7 : B_n^{[\text{real}]} \leq \chi, \forall n \in L_b, \)

\( C8 : W_k \succeq 0, \forall k \in L_i. \)

The Algorithm 1 summarizes the steps of updating the weight factor \( \xi_{zk} \) and iteratively finding the solutions to the optimization problem (3.10), where the cooperative links between the RRHs and the ITs are iteratively removed, corresponding to the RRHs with shortage of power budget.

**Algorithm 1 Reweighted \( \ell_1 \)-norm method for ITs**

1: **Initialize**: constant \( \mu \to 0, \) iteration count \( t = 0, \) weight factor \( \xi_{zk}(t) = 1, \) maximum number of iterations \( t_{\text{max}}, \)

2: **while** \( \xi_{zk} \) is not converged or \( t \neq t_{\text{max}} \) **do**

3: Find the optimal beamformers \( w_{nk}(t) \) by solving (3.10);

4: Update the weight factor \( \xi_{zk}(t+1) \) as follows,

\[ \xi_{zk}(t+1) = \frac{1}{\|w_{nk}(t)\|_2^2 + \mu} \]

5: Increment the iteration number \( t = t + 1; \)

6: **end while**
3.4 Strategy 2: Power-Shortage Management by Full Cooperation

3.4.1 Problem Formulation

Distinct from the Strategy 1 that enables partial coordination by setting a set of $w_{zk} = 0$ in (3.7) according to the power restriction, the Strategy 2 preserves all the joint transmission links between the RRHs and the ITs.

\[ \text{Power-shortage ?} \]
\[ \text{Reduce total transmit power} \]
\[ \text{(Full Cooperation)} \]

\[ \text{Renewable energy} \]
\[ \text{harvesting devices} \]

\[ \text{RRH} \]

\[ \text{Figure 3.2: Power-shortage management by full cooperation in the green C-RAN.} \]

As shown in Figure 3.2, Strategy 2 minimize a linear combination of the total transmit power of the RRHs with shortage of power budget and the maximum power purchased from the real-time market, under the constraint of maintaining the required QoS by the ITs to reduce the total energy cost of the network operator,
3.4. Strategy 2: Power-Shortage Management by Full Cooperation

which can be formulated as

\[
\begin{align*}
\min_{w, B_n^{\text{real}}} & \quad \beta \sum_{z \in \mathcal{Z}} P^{\text{Tx}}_z + \max_{n \in \mathcal{L}_b} \left\{ B_n^{\text{real}} \right\} \\
\text{s.t.} & \quad C1 : \text{SINR}_k \geq \gamma_k, \quad \forall k \in \mathcal{L}_i, \\
& \quad C2 : P^{\text{Tx}}_n + P^{\text{circuit}}_n \leq E_n + B^{\text{ahead}}_n + B^{\text{real}}_n - S_n, \quad \forall n \in \mathcal{L}_b, \\
& \quad C3 : P^{\text{Tx}}_n \leq P^{\text{Tmax}}_n, \quad \forall n \in \mathcal{L}_b, \\
& \quad C4 : \sum_{n \in \mathcal{L}_b} B^{\text{ahead}}_n + \sum_{n \in \mathcal{L}_b} B^{\text{real}}_n \leq P^{\text{max}}_{\text{CP}} - P^{\text{circuit}}_{\text{CP}}, \quad \forall n \in \mathcal{L}_b, \\
& \quad C5 : B^{\text{real}}_n \geq 0, \quad \forall n \in \mathcal{L}_b, \\
& \quad C6 : S_n \geq 0, \quad \forall n \in \mathcal{L}_b,
\end{align*}
\]

(3.11)

where \(\beta\) is a constant that indicates the precedence of the CP for the total transmit power of RRHs with power shortage. Please note the difference between the problem formulation for Strategy 2 in (3.11) and the problem formulation for Strategy 1 in (3.6) is the left hand side (LHS) of the both proposed objective functions. The second strategy only reducing the total transmit power of the RRHs with shortage of power budget, i.e., \(\sum_{z \in \mathcal{Z}} P^{\text{Tx}}_z\), \(\mathcal{Z} \subset \mathcal{L}_b\), where the \(z\)-th RRH is in power budget shortage. This strategy maintains the advantages of full cooperation scheme by secures all the joint transmission links between the RRHs and the ITs. On the contrary, Strategy 1 applies sparse beamforming technique to enables partial cooperation for the RRHs with shortage of power budget.

For the fair comparison, all the contraints set in the Strategy 2 are similar to the constraints set in Strategy 1. C1 denotes a set of QoS constraints for \(K_i\) ITs. C2 indicates that the total transmit power of each RRH, i.e., \(P^{\text{Tx}}_n = \sum_{k \in \mathcal{L}_i} ||w_{nk}||^2_2, n \in \mathcal{L}_b\), is constrained by the total available power \(P^{\text{total}}_n\) and the hardware circuit power consumption \(P^{\text{circuit}}_n\) at the respective RRH, in accordance with (3.1). C3 represents that the total transmit power should not exceed the maximum transmit power allowance, denoted by \(P^{\text{Tmax}}_n\), at the \(n\)-th RRH. C4 specifies the constraint for the total power supplied by the CP to the RRHs, where \(P^{\text{circuit}}_{\text{CP}}\) and \(P^{\text{max}}_{\text{CP}}\) are the hard-
ware circuit power consumption at the CP and the maximum power provision at the CP, respectively. C5 and C6 are the non-negative constraints set for the optimization variables.

### 3.4.2 Convex Relaxation

Following the similar SDR approach as in the strategy 1 by substituting (3.9) into (3.11) and defining $W_k = w_kw_k^H$ and $H_k = h_kh_k^H$, the original optimization problem can be formulated as a SDP problem. Then, by applying the SDR approach to relax the rank-one constraints of $\text{rank}(W_k) \leq 1$, the non-convex problem of Strategy 2 in (3.11) can be transformed as

$$\begin{align*}
\min_{W_k, z} & \quad \beta \left( \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{L}_i} \text{tr}(W_kD_z) \right) + \chi \\
\text{s.t.} & \quad C1 : \gamma_k^{-1}\text{tr}(H_kW_k) \geq \sum_{j \neq k} \text{tr}(H_kW_j) + \sigma_k^2, \quad \forall k \in \mathcal{L}_i, \\
& \quad C2 : \sum_{k \in \mathcal{L}_i} \text{tr}(W_kD_n) \leq E_n + B_n^{[\text{ahead}]} + B_n^{[\text{real}]} - S_n - P_n^{[\text{circuit}]}, \quad \forall n \in \mathcal{L}_b, \\
& \quad C3 : \sum_{k \in \mathcal{L}_i} \text{tr}(W_kD_n) \leq P_n^{[\text{Tmax}]}, \quad \forall n \in \mathcal{L}_b, \\
& \quad C4 : \sum_{n \in \mathcal{L}_b} B_n^{[\text{ahead}]} + \sum_{n \in \mathcal{L}_b} B_n^{[\text{real}]} \leq P_{\text{CP}}^{[\text{max}]} - P_{\text{CP}}^{[\text{circuit}]}, \\
& \quad C5 : B_n^{[\text{real}]} \geq 0, \quad \forall n \in \mathcal{L}_b, \\
& \quad C6 : S_n \geq 0, \quad \forall n \in \mathcal{L}_b, \\
& \quad C7 : B_n^{[\text{real}]} \leq \chi, \quad \forall n \in \mathcal{L}_b, \\
& \quad C8 : W_k \succeq 0, \quad \forall k \in \mathcal{L}_i.
\end{align*}$$
3.5 Strategy 3: Overall Network Energy Management by Full Cooperation

3.5.1 Problem Formulation

This strategy reduces the total energy cost of the network operator by minimizing a linear combination of the total transmit power of all the RRHs and the maximum power purchased from the real-time market, under the constraint of maintaining the required QoS by the ITs, regardless of shortage of power budget in the RRHs, which can be formulated as

$$\min_{w_k, B_n^{\text{real}}}|\begin{align*}
\zeta \sum_{n \in \mathcal{L}_b} P_n^{\text{Tx}} &+ \delta \max_{n \in \mathcal{L}_b} \{B_n^{\text{real}}\} \\
\end{align*}|$$

subject to

$$C1: \text{SINR}_k \geq \gamma_k, \quad \forall k \in \mathcal{L}_i,$$

$$C2: P_n^{\text{Tx}} + P_n^{\text{circuit}} \leq E_n + B_n^{\text{ahead}} + B_n^{\text{real}} - S_n, \quad \forall n \in \mathcal{L}_b,$$

$$C3: P_n^{\text{Tx}} \leq P_n^{\text{Tmax}}, \quad \forall n \in \mathcal{L}_b,$$

$$C4: \sum_{n \in \mathcal{L}_b} B_n^{\text{ahead}} + \sum_{n \in \mathcal{L}_b} B_n^{\text{real}} \leq P_{\text{CP}}^{\text{max}} - P_{\text{CP}}^{\text{circuit}}, \quad \forall n \in \mathcal{L}_b,$$

$$C5: B_n^{\text{real}} \geq 0, \quad \forall n \in \mathcal{L}_b,$$

$$C6: S_n \geq 0, \quad \forall n \in \mathcal{L}_b,$$

where $\zeta$ and $\delta$ are constants and indicate, respectively, the precedence of the CP for the total transmit power and the maximum power purchased from the real-time market. Note that if $\zeta = 1$ and $\delta = 0$ is set, the strategy 3 will denote a baseline scheme that the cooperative transmission in C-RAN and energy trading are separately optimized.

Furthermore, the difference between the problem formulation for Strategy 3 as compared to the previous problem formulations, i.e., (3.6) and (3.11) is also at the LHS of its objective functions. With the aim to reduce the total cost of the network operator, the third strategy proposed a model to minimize the total transmit power of all the RRHs depending on their power budgets. In the other words, if the RRH has
lowest level of power budget, it will transmit lowest power to all the ITs while the RRH with higher level of power budget will transmit more power to all the ITs in the green C-RAN. Note that Strategy 3 and Strategy 2 are based on full cooperation scheme by secures all the joint transmission links between the RRHs and the ITs in the green C-RAN. For the fair comparison, all the contraints set in this strategy are also similar to the constraints set in Strategy 1 and Strategy 2. C1 denotes a set of QoS constraints for $K_i$ ITs. C2 indicates that the total transmit power of each RRH, i.e., $P_{n}^{[\text{Tx}]} = \sum_{k \in \mathcal{L}_i} ||w_{nk}||^2_2, n \in \mathcal{L}_b$, is constrained by the total available power $P_{n}^{[\text{total}]}$ and the hardware circuit power consumption $P_{n}^{[\text{circuit}]}$ at the respective RRH, in accordance with (3.1). C3 represents that the total transmit power should not exceed the maximum transmit power allowance, denoted by $P_{n}^{[T_{max}]}$, at the $n$-th RRH. C4 specifies the constraint for the total power supplied by the CP to the RRHs, where $P_{CP}^{[\text{circuit}]}$ and $P_{CP}^{[\text{max}]}$ are the hardware circuit power consumption at the CP and the maximum power provision at the CP, respectively. C5 and C6 are the non-negative constraints set for the optimization variables.
3.5.2 Convex Relaxation

Following the similar steps as in the strategy 2, the strategy 3 in (3.13) can be reformulated as

$$\min_{W_k, \zeta} \left( \sum_{n \in \mathcal{L}_b} \sum_{k \in \mathcal{L}_i} \text{tr}(W_k D_n) \right) + \chi$$

(3.14)

s.t. C1: $$\gamma_k^{-1} \text{tr}(H_k W_k) \geq \sum_{j \neq k} \text{tr}(H_k W_j) + \sigma_k^2, \quad \forall k \in \mathcal{L}_i,$$

C2: $$\sum_{k \in \mathcal{L}_i} \text{tr}(W_k D_n) \leq E_n + B_n^{[\text{ahead}]} + B_n^{[\text{real}]} - S_n - P_n^{[\text{circuit}]}, \quad \forall n \in \mathcal{L}_b,$$

C3: $$\sum_{k \in \mathcal{L}_i} \text{tr}(W_k D_n) \leq P_n^{[\text{Tmax}]}, \quad \forall n \in \mathcal{L}_b,$$

C4: $$\sum_{n \in \mathcal{L}_b} B_n^{[\text{ahead}]} + \sum_{n \in \mathcal{L}_b} B_n^{[\text{real}]} \leq P_{\text{CP}}^{[\text{max}]} - P_{\text{CP}}^{[\text{circuit}]},$$

C5: $$B_n^{[\text{real}]} \geq 0, \quad \forall n \in \mathcal{L}_b,$$

C6: $$S_n \geq 0, \quad \forall n \in \mathcal{L}_b,$$

C7: $$\delta B_n^{[\text{real}]} \leq \chi, \quad \forall n \in \mathcal{L}_b,$$

C8: $$W_k \succeq 0, \quad \forall k \in \mathcal{L}_i.$$

Note that, the SDP problem in (3.10), (3.12) and (3.14) can be efficiently solved via interior point methods, e.g., CVX [108]. Furthermore, if the obtained solutions for $$W_k$$ are rank-one, the problems (3.10), (3.12) and (3.14) yield same optimal solutions as in problem (3.6), (3.11) and (3.13), respectively. When the rank is greater than one, the standard Gaussian randomization method [109] can be employed to reconstruct the rank-one suboptimal solutions to the beamforming vectors.

3.6 Simulation Results

The simulation considers a C-RAN consists of $$N = 3$$ neighbouring RRHs, each equipped with $$M = 8$$ antennas, transmitting to $$K_i = 6$$ single antenna ITs that are randomly generated in the network. The renewable energy generated from environmental sources at each local RRH is $$E_1 = 3.5W, E_2 = 0.2W$$ and $$E_3 = 0.5W$$, respectively. Let’s further assume that the network operator has purchased
3.6. Simulation Results

\[ B_{1}^{[\text{ahead}]} = B_{2}^{[\text{ahead}]} = B_{3}^{[\text{ahead}]} = 1.5 \text{W amount of energy from the day-ahead market at the price of } \pi^{[\text{ahead}]} = £0.07 \text{ per unit energy. If the energy is insufficient, the network operator can purchase additional energy from the real-time market at higher price of } \pi^{[\text{real}]} = £0.15 \text{ per unit energy while in the opposite case, the excessive energy can be sold back to the grid at a reduced price of } \pi^{[\text{sell}]} = £0.05 \text{ per unit energy. For simplicity, let set } P_{n}^{[\text{circuit}]} = 30 \text{dBm}, P_{CP}^{[\text{circuit}]} = 40 \text{dBm}, P_{CP}^{[\text{max}]} = 50 \text{dBm} \text{ and } P_{n}^{[\text{Tmax}]} = 46 \text{dBm. Moreover, the distance between two adjacent RRHs is } D = 500 \text{m, and the channel bandwidth is chosen to be 20 MHz. A correlated channel model is implemented, as suggested in [57], as } h_{nk} = R_{nk}^{1/2} h_{w}, \text{ where } h_{w} \in \mathbb{C}^{M \times 1} \text{ are zero mean circularly symmetric complex Gaussian (ZMC-SCG) random variables with unit variance, } R_{nk} \in \mathbb{C}^{M \times M} \text{ is the spatial covariance matrix between the } n\text{-th RRH and the } k\text{-th IT, and the } (m,n)\text{-th element is given by } R_{nk} = G_{a} L_{nk} \sigma^{2} \left( \frac{\sigma_{s} \ln 10}{100} \right)^{2} e^{2 \frac{2 \delta \sigma}{\lambda} \left[ \left( n-m \right) \sin \theta_{nk} \right]} \cos \theta_{nk} \right)^{2} e^{2 \frac{2 \sigma_{s}}{\lambda} \left[ \left( n-m \right) \cos \theta_{nk} \right]^{2}}, \text{ where } G_{a} = 15 \text{dBi is the antenna gain, } L_{nk}(\text{dB}) = 125.2 + 36.3 \log_{10}(d) \text{ is the path loss between the } n\text{-th RRH and the } k\text{-th IT, as suggested in 3GPP [63], } \sigma^{2} \text{ is the variance of the complex Gaussian fading coefficient, } \sigma_{s} = 8 \text{dB is the standard deviation of the log-normal fading (shadowing), } \delta = \lambda / 2 \text{ is the spacing between two adjacent antenna elements, } \lambda \text{ is the wavelength of the carrier, } \sigma = 2^\circ \text{ is the angular offset standard deviation and } \theta_{nk} \text{ is the estimated angle of departure between the } n\text{-th RRH and the } k\text{-th IT. The list of parameters used in this simulation are summarized in Table 3.1. The simulation results are averaged over 200 independent channel realizations.}

Note that in Strategy 2, \( \beta \) is a constant that indicates the precedence of the CP for the total transmit power of RRHs with power shortage. This strategy minimize a linear combination of the total transmit power of the RRHs with shortage of power budget and the maximum power purchased from the real-time market, under the constraint of maintaining the required QoS by the ITs to reduce the total energy cost of the network operator. Strategy 2(\( \beta = 1 \)) and Strategy 2(\( \beta = 10 \)) have been chosen to study the impact of different weighting factor on the RRHs with shortage of power budget. Figure 3.3 compares the performance of the proposed three joint cooperative energy trading strategies with different parameter settings against the
Table 3.1: Simulation parameters for Chapter 3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of RRHs ($N$)</td>
<td>3</td>
</tr>
<tr>
<td>Number of antennas per RRH ($M$)</td>
<td>8</td>
</tr>
<tr>
<td>Number of ITs ($K_i$)</td>
<td>6</td>
</tr>
<tr>
<td>Amount of renewable energy generated at the $n$-th RRH</td>
<td>$E_1 = 3.5\text{W}, E_2 = 0.2\text{W}$</td>
</tr>
<tr>
<td></td>
<td>$E_3 = 0.5\text{W}$</td>
</tr>
<tr>
<td>Amount of energy purchased from the day-ahead market for the $n$-th RRH</td>
<td>$B_1^{\text{[ahead]}} = B_2^{\text{[ahead]}} =$</td>
</tr>
<tr>
<td></td>
<td>$B_3^{\text{[ahead]}} = 1.5\text{W}$</td>
</tr>
<tr>
<td>Price of energy purchased from the day-ahead market ($\pi^{\text{[ahead]}}$)</td>
<td>£0.07 per unit energy</td>
</tr>
<tr>
<td>Price of energy purchased from the real-time market ($\pi^{\text{[real]}}$)</td>
<td>£0.15 per unit energy</td>
</tr>
<tr>
<td>Price of energy sold to the grid ($\pi^{\text{[sell]}}$)</td>
<td>£0.05 per unit energy</td>
</tr>
<tr>
<td>Distance between two adjacent RRHs ($D$)</td>
<td>500 m</td>
</tr>
<tr>
<td>Channel bandwidth’s wide</td>
<td>20 MHz</td>
</tr>
<tr>
<td>Circuit power consumption at the CP ($P_{\text{CP}}^{\text{[circuit]}}$)</td>
<td>40 dBm</td>
</tr>
<tr>
<td>Maximum power provision at the CP ($P_{\text{CP}}^{\text{[max]}}$)</td>
<td>50 dBm</td>
</tr>
<tr>
<td>Circuit power consumption at the $n$-th RRH ($P_{n}^{\text{[circuit]}}$)</td>
<td>30 dBm</td>
</tr>
<tr>
<td>Maximum transmit power allowance ($P_{n}^{\text{Tmax}}$)</td>
<td>46 dBm</td>
</tr>
<tr>
<td>Array antenna gain ($G_a$)</td>
<td>15 dBi</td>
</tr>
<tr>
<td>Noise power spectral density</td>
<td>$-174 \text{dBm/Hz}$</td>
</tr>
<tr>
<td>Noise figure at receiving terminals</td>
<td>5 dB</td>
</tr>
<tr>
<td>Path loss model over a distance of $d$ km</td>
<td>$125.2 + 36.3 \log_{10}(d)$</td>
</tr>
<tr>
<td>Angular offset standard deviation ($\sigma$)</td>
<td>$2^\circ$</td>
</tr>
<tr>
<td>Log-normal shadowing standard deviation ($\sigma_s$)</td>
<td>8 dB</td>
</tr>
<tr>
<td>Spacing between two adjacent antenna elements ($\delta$)</td>
<td>$\lambda / 2$</td>
</tr>
<tr>
<td>Simulation results are averaged over a number of independent channel realizations</td>
<td>200</td>
</tr>
</tbody>
</table>
3.6. Simulation Results

baseline scheme that separately optimize the cooperative transmission and energy trading, in terms of averaged total transmit power. It can be observed that the strategy 3 ($\zeta = 1, \delta = 1$) and the baseline scheme perform closely and overwhelmingly better than the other strategies up to medium SINR range, due to the objective of total transmit power minimization. Nevertheless, all three proposed strategies converge towards the baseline scheme in terms of total transmit power when achieving higher SINR requirements, until the power constraints at individual RRHs and the CP are attained.

Figure 3.4 illustrates the behaviour of transmit power from RRH2 that is in power shortage, towards the individual ITs at $\gamma = 25$dB SINR target for different strategies. One can observe from the figure that for the strategy 1, only the cooperative link between RRH2 and the 3rd IT is preserved while RRH2 is not participating in the joint transmission to the other ITs due to its power restriction. Meantime, the strategies 2 and 3 retain all the joint transmission links between RRH2 and the ITs. However, for the strategy 2, the RRH2 concentrates on serving the 3rd IT while allocating least transmit power to the other ITs based on its power budget.

![Figure 3.3: Comparison of total transmit power for different strategies](image)

Figure 3.3: Comparison of total transmit power for different strategies
3.6. Simulation Results

Figure 3.4: Comparison of behaviour of transmit power from RRH2 to individual ITs for different strategies at target SINR of $\gamma = 25$ dB

Figure 3.5: Comparison of total energy cost for different strategies

Comparison of total energy cost of the network operator versus various SINR targets for different strategies is shown in Figure 3.5. One can conclude that in terms
of total energy cost reduction, overwhelming performance gain can be achieved by all three proposed joint cooperative energy trading strategies as compared to the baseline scheme. The strategy 2 ($\beta = 1$) has the lowest total energy cost in terms of achieving higher SINR targets and closely follows strategy 3 at low and medium SINR requirements. Both of strategies 2 and 3 outperform the strategy 1 in terms of reducing the total energy cost.

3.7 Concluding Remarks

In this chapter, three different cooperative real-time energy trading strategies have been proposed for downlink green C-RAN, to jointly minimize the energy consumption and the real-time energy trading under the constraints of demand and supply power balancing at RRHs and QoS required by ITs. For strategy 1, a sparse beamforming problem is formulated as an $\ell_0$-norm optimization problem and solve it using SDR and iterative reweighted $\ell_1$-norm approximation of $\ell_0$-norm. The strategies 2 and 3 are formulated as numerically tractable optimization problem and solved using the SDR approach. Simulation results confirm that in terms of reducing total energy cost of the network operator, significant performance gain can be achieved by all three proposed joint cooperative transmission and energy trading strategies, as compared to a baseline scheme that separately optimize the cooperative transmission and energy trading in a C-RAN scenario with realistic parameter settings.
Chapter 4

Real-Time Energy Management in Fronthaul Constrained Green C-RAN

4.1 Introduction

In the practical downlink cloud radio access network (C-RAN), the tremendous information exchange between the centralized cloud computing processor (CP) and the remote radio heads (RRHs) via capacity-constrained fronthaul links may result in the infeasibility of full cooperation. Therefore, it is necessary to take into account of the fronthaul capacity restrictions and employ sparse beamforming technique to enable partial cooperation. However, the degree of partial cooperation among the RRHs in serving the receiving terminals and the total transmit power minimization conflict with each other. In particular, reducing the receiving terminal-RRH cooperative links may be beneficial for fronthaul link capacity relaxation, it will, nevertheless, result in an increase in the total transmit power. In the sequel, a joint strategy of cooperative resource management and real-time energy trading is proposed to strike an optimum balance between the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, RRHs’ total transmit power and their maximum or overall energy-purchase from real-time market under the constraints of fronthaul link capacity restrictions. As shown in
4.1. Introduction

Figure 4.1, it is assumed that the CP is frequently updated with power budgets of the individual RRHs. Subsequently, the optimal receiving terminal cluster to be served by each RRH is determined by the CP through evaluation of actual situations, i.e., the location of active energy receiving terminals (ETs) and information receiving terminals (ITs), the associated channel conditions, the available resources, power budgets, and fronthaul link capacity constraints of the individual RRHs.

Two sparse beamforming optimization problems are introduced, namely, Dynamic RRH-centric Clustering (DRRHC) with Min-Max Real-time Energy Purchase clustering and Dynamic RRH-centric Clustering (DRRHC) with Overall Energy Purchase Minimization. More specifically, two sparse optimization problems are formulated and applies reweighted $\ell_1$-norm approximation for $\ell_0$-norm and semidefinite relaxation (SDR) to develop two iterative algorithms for the proposed
strategies.

In contrast to the energy management model proposed in the previous chapter as well as in [18], this chapter integrates a real-time energy trading strategy with simultaneous wireless information and power transfer (SWIPT) concept, where the RRHs simultaneously transfer information beams to information receiving terminals and energy beams to active energy receiving terminals. Since energy could be highly attenuated over a long distance propagation and in order to maintain the efficiency of SWIPT, an iterative ET authorization algorithm that allows only those ETs situated close enough to the RRHs to receive wireless energy is introduced.

Instead of designing the sparse beamforming for individual RRHs with a shortage of power proposed in Chapter 3, [18] and [21], the design strategies introduced in this chapter account for all RRHs with or without a shortage of power. The proposed strategies strike an optimum balance between the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, RRHs’ total transmit power and their maximum or total energy-purchase from the real-time market. More specifically, this chapter introduces two strategies for optimizing the RRHs’ real-time energy trading with the grid via: (1) minimizing the RRHs’ maximum real-time energy-purchase requests; (2) minimizing the RRHs’ overall energy-purchase requests from the real-time market.

Unlike Chapter 3 and the latest papers for energy trading with grid, e.g., [7, 18, 21], that take no consideration of realistic constraints on fronthaul capacity restrictions, this chapter formulates more realistic scenarios where RRHs are constrained with limited fronthaul capacities. In practice, the fronthaul resources are highly limited, especially, for joint transmission where all the users data are circulated among all the RRHs. Hence, the designs that take no consideration of fronthaul capacity constraints in problem formulation may lead to infeasible solutions in practical scenarios.

The problem formulations naturally lead to computationally intractable optimization problems which are dealt with in this chapter by reformulating the original problems in their alternative tractable forms using rank relaxation technique,
i.e., SDR. The application of SDR adds a non-convex unit-rank constraints to the alternative optimization problems, which are subsequently relaxed to find tractable solutions. However, a randomization technique [60] which is a computationally intensive search is required to pick only those feasible solutions that are unit-rank. Attached in the Appendix A, this chapter analytically proves that the solutions to the alternatively reformulated optimization problems using SDR are always unit-rank and, hence, no subsequent search is required to find the unit-rank solutions.

4.1.1 Organization

The remainder of this chapter is organized as follows. Section 4.2 introduces the system model and an iterative ET authorization algorithm. In section 4.3, the DR-RHC with min-max energy purchase strategy is formulated, and then transformed into numerically tractable form using reweighted $\ell_1$-norm method and the SDR. In section 4.4, the DRRHC with overall energy purchase minimization strategy is proposed, and then transformed into numerically tractable form using reweighted $\ell_1$-norm method and the SDR. Numerical simulation results are analyzed in section 4.5. Finally, section 4.6 summarizes the chapter.

4.2 System Model

This work considers a downlink C-RAN with SWIPT from $N$ RRHs, equipped with $M$ antennas, towards $K_i$ active single-antenna ITs and $K_e$ active single-antenna ETs, respectively, over the same frequency band. A CP is the core processing unit in the network that coordinates all the cooperative strategies, e.g., cooperative energy trading, for the RRHs based on perfect knowledge of channel state information and real-time supply and demand power balancing. Besides, the CP also has accessibility to the data of all the ITs and distributes it along with beamformers, to the corresponding RRHs via fronthaul links and collect the energy information, i.e., the energy harvesting rates and energy buying/selling prices via the smart meters installed at RRHs and the grid-deployed communication/control links connecting them. Let $\mathcal{L}_b = \{1, \cdots, N\}$, $\mathcal{L}_e = \{1, \cdots, K_e\}$, $\mathcal{L}_e^{[idle]} = \{1, \cdots, K_e^{[idle]}\}$ and $\mathcal{L}_i = \{1, \cdots, K_i\}$ indicate, respectively, the set of indexes of the RRHs, the active ETs, the idle ETs
and the active ITs. It is further assumed that the energy transmission between the CP and the RRHs is accomplished via dedicated power lines.

4.2.1 Downlink Transmission Model

The aggregate beamforming vector from all the RRHs towards the $i$-th IT, $i \in \mathcal{L}_i$, as $\mathbf{w}_i = [\mathbf{w}_{1i}^H, \ldots, \mathbf{w}_{Ni}^H]^H \in \mathbb{C}^{MN \times 1}$ is denoted, where $\mathbf{w}_{ni} \in \mathbb{C}^{M \times 1}$ is the beamformer from the $n$-th RRH towards the $i$-th IT. $\mathbf{v}_e = [\mathbf{v}_{1e}^H, \ldots, \mathbf{v}_{Ne}^H]^H \in \mathbb{C}^{MN \times 1}$ represents the aggregate beamforming vector from all the RRHs to the $e$-th active ET. Similarly, let $\mathbf{h}_{ni} \in \mathbb{C}^{M \times 1}$ represent the channel vector between the $n$-th RRH and the $i$-th IT, the aggregate channel vector between all the RRHs and the $i$-th IT is denoted by $\mathbf{h}_i = [\mathbf{h}_{1i}^H, \ldots, \mathbf{h}_{Ni}^H]^H \in \mathbb{C}^{MN \times 1}$. The received signals at the $i$-th IT, $i \in \mathcal{L}_i$, is then given by

$$y_i = \mathbf{h}_i^H \mathbf{w}_i s_i^{[\text{IT}]} + \sum_{j \neq i, j \in \mathcal{L}_i} \mathbf{h}_i^H \mathbf{w}_j s_j^{[\text{IT}]} + \sum_{e \in \mathcal{L}_e} \mathbf{h}_i^H \mathbf{v}_e s_e^{[\text{ET}]} + n_i, \quad (4.1)$$

where the terms at the right hand side of (4.1), respectively, represent the intended information-carrying signal for the $i$-th IT, the inter-user interference caused by all other non-desired information beams, the interference caused by energy beams for all active ETs and the additive white Gaussian noise, i.e., $n_i \sim \mathcal{CN}(0, \sigma_i^2)$, at the $i$-th IT. Since no information is carried by the energy-carrying signals, they can be any arbitrary random signals. Without loss of generality, it is assumed that $\mathbb{E}(s_i^{[\text{IT}]}) = \mathbb{E}(s_e^{[\text{ET}]}) = 1$ and $\sigma_i^2$ is identical at all receiving terminals. Then, the signal-to-interference-plus-noise ratio (SINR) at the $i$-th IT, $i \in \mathcal{L}_i$, is formulated as

$$\text{SINR}_i^{[\text{IT}]} = \frac{\mathbf{h}_i^H \mathbf{w}_i}{\sum_{j \in \mathcal{L}_i, j \neq i} |\mathbf{h}_j^H \mathbf{w}_j|^2 + \sum_{e \in \mathcal{L}_e} |\mathbf{h}_i^H \mathbf{v}_e|^2 + \sigma_i^2}. \quad (4.2)$$

The fronthaul capacity consumption for the $n$-th RRH is given by

$$C_n^{[\text{fronthaul}]} = \sum_{i \in \mathcal{L}_i} \|\mathbf{w}_{ni}\|_2 R_i = \sum_{i \in \mathcal{L}_i} \|\mathbf{w}_{ni}\|_2^2 R_i, \quad \forall n \in \mathcal{L}_b, \quad (4.3)$$
where \( R_i = \log_2(1 + \text{SINR}_i^{[\text{IT}]} ) \) is the achievable data rate (bit/s/Hz) for the \( i \)-th IT. Note that the quantity of \( \ell_0 \)-norm in (4.3) is invariant when the input arguments are squared and \( \| \| w_{ni} \|_2 \|_0 \) is an indicator function that illustrates the scheduling choices of the individual ITs, i.e.,

\[
\| \| w_{ni} \|_2 \|_0 = \begin{cases} 
0, & \text{if } \| w_{ni} \|_2^2 = 0, \\
1, & \text{if } \| w_{ni} \|_2^2 \neq 0.
\end{cases}
\] (4.4)

Note that \( \| w_{ni} \|_2^2 = 0 \) indicates partial cooperation, where the CP will not deliver data for the \( i \)-th IT to the \( n \)-th RRH via the corresponding fronthaul link and the \( n \)-th RRH is not participating in the joint transmission to the \( i \)-th IT.

### 4.2.2 An Iterative ET Authorization Algorithm

Motivated by the fact that energy is highly attenuated during long-distance propagation and in order to improve the energy efficiency, an ET authorization algorithm that can be implemented in the CP to authorize the RRHs to transmit energy directly towards the ETs located within their hexagonal energy serving area and set as active ETs is considered, whilst other ETs will be set as idle ETs. Note that only the active ETs will be assigned with dedicated beamformers for power transmission. Consequently, the active ETs can harvest energy not only from the RRHs, but also from the ambient RF signals whilst the idle ETs merely harvest energy from the surroundings. The steps of authorization are summarized in Algorithm 2.

By adjusting the value of \( \varphi_{nm} \), the size of the hexagonal energy serving area can be controlled by the CP as per practical situations, e.g., capacity restrictions and power budgets. Then, the total energy harvested by the \( e \)-th active ET, \( e \in \mathcal{L}_e \), can be expressed as

\[
\mathcal{G}_e^{[\text{ET}]} = \eta \left( |g_{He}^H v_e|^2 + \sum_{j \in \mathcal{L}_e, j \neq e} |g_{He}^H v_j|^2 + \sum_{i \in \mathcal{L}_i} |g_{He}^H w_i|^2 \right),
\] (4.5)

where \( 0 \leq \eta \leq 1 \) indicates the conversion efficiency from the harvested RF energy to the electrical energy and is assumed to be constant and identical for all ETs; \( g_c = [g_{He}^H, \ldots, g_{Ne}^H]^H \in \mathbb{C}^{MN \times 1} \) represents the aggregate channel vector from all the
4.3. Strategy 1: DRRHC with Min-Max Real-time Energy Purchase

Algorithm 2: An iterative ET authorization algorithm

1. Initialize: RRH-to-RRH distance $D$ and constant $\varphi_{nm}$
2. for $m = 1 : (K_e + K_e^{[\text{idle}]})$
3. for $n = 1 : N$
4. CP calculates the hexagonal energy serving areas of the $n$-th RRH for the $m$-th ET as follows
   \[ A_{nm} = \varphi_{nm} \ast 6\left(\frac{(D/2)^2}{\sqrt{3}}\right); \]
5. if the $m$-th ET locates within the area $A_{nm}$
6. then the $m$-th ET is set as an active ET and is permitted to harvest energy from
7. the $n$-th RRH, set $\{w_{lm}\}_{l \neq n} = 0$;
8. end if
9. if the $m$-th ET locates outside the area $A_{nm}, \forall n \in \mathcal{L}_b$
10. then the $m$-th ET is prohibited to harvest energy from any RRH, set as an
11. idle ET;
12. end if
13. end for
14. end for

RRHs to the $e$-th active ET. Note that only one RRH is serving the $e$-th active ET and all the beamformers from other RRHs to the $e$-th ET are set to be zero as per step 6 in the Algorithm 2. Besides, the total amount of energy that can be harvested from surroundings by the $z$-th idle ET, $z \in \mathcal{L}_e^{[\text{idle}]}$, is given by

\[
G_z^{[\text{ET-idle}]} = \eta\left( \sum_{i \in \mathcal{L}_i} \left| f_i^H w_i \right|^2 + \sum_{e \in \mathcal{L}_e} \left| f_e^H v_e \right|^2 \right),
\]

(4.6)

where $f_z = [f_{1z}^H, \cdots, f_{Nz}^H]^H \in \mathbb{C}^{MN \times 1}$ denotes the aggregate channel vector from all the RRHs to the $z$-th idle ET.

4.3 Strategy 1: DRRHC with Min-Max Real-time Energy Purchase

4.3.1 Problem Formulation

Strategy 1 is formulated as a linear combination of the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, the RRHs’ total transmit power and the maximum real-time energy-purchase from the grid, under the constraints of supply and demand power balancing at the RRHs, the
4.3. Strategy 1: DRRHC with Min-Max Real-time Energy Purchase

individual fronthaul link capacity restrictions, the quality of service (QoS) requirements at the ITs, and the transmission energy requirements at the ETs, i.e.,

\[ \min_{w_{ni}, v_{ne}, B_{n}^{\text{real}}} \alpha \varphi^{\text{coop}} + \beta \sum_{n \in L_b} P_{n}^{\text{Tx}} + \zeta \max_{n \in L_b} \left\{ B_{n}^{\text{real}} \right\} \] (4.7)

\[ \text{s.t. } \]
\[ C1: \text{SINR}_{i}^{\text{IT}} \geq \gamma_{i}, \quad \forall i \in L_i, \]
\[ C2: \varphi^{\text{ET}} \geq P_{e}^{\text{min}}, \quad \forall e \in L_e, \]
\[ C3: \varphi^{\text{ET-idle}} \geq P_{z}^{\text{idle}}, \quad \forall z \in L_{e}^{\text{idle}}, \]
\[ C4: P_{n}^{\text{Tx}} \leq E_{n} + B_{n}^{\text{ahead}} + B_{n}^{\text{real}} - S_{n} - P_{n}^{\text{circuit}}, \quad \forall n \in L_b, \]
\[ C5: P_{n}^{\text{Tx}} \leq P_{n}^{\text{Tmax}}, \quad \forall n \in L_b, \]
\[ C6: \sum_{n \in L_b} B_{n}^{\text{ahead}} + \sum_{n \in L_b} B_{n}^{\text{real}} \leq P_{CP} - P_{CP}^{\text{circuit}}, \]
\[ C7: B_{n}^{\text{real}} \geq 0, \quad \forall n \in L_b, \]
\[ C8: S_{n} \geq 0, \quad \forall n \in L_b. \]

where \( \varphi^{\text{coop}} = (\sum_{i \in L_i} \| w_{ni} \|_2^2 + \cdots + \sum_{i \in L_i} \| w_{Ni} \|_2^2) + (\sum_{e \in L_e} \| v_{1e} \|_2^2 + \cdots + \sum_{e \in L_e} \| v_{Ne} \|_2^2) \) indicates the number of total active cooperative links between the RRHs and the receiving terminals, \( \alpha \geq 0 \) is the maximum power cost in the fronthaul due to the transportation of an active receiving terminal’s data from the CP to a serving RRH and \( P_{n}^{\text{Tx}} = \sum_{i \in L_i} \| w_{ni} \|_2^2 + \sum_{e \in L_e} \| v_{ne} \|_2^2, n \in L_b \) is the total transmit power by the \( n \)-th RRH to its scheduled receiving terminals. The weighting coefficients \( \beta \geq 0 \) and \( \zeta \geq 0 \) model the degrees of CP’s emphasis on minimizing the total transmit power, i.e., \( \sum_{n \in L_b} P_{n}^{\text{Tx}} \), and the maximum real-time energy-purchase from grid, i.e., \( \max_{n \in L_b} \left\{ B_{n}^{\text{real}} \right\} \), respectively. A larger weighting coefficient results in a more emphasize in minimizing the corresponding term of the objective function. Let \( \gamma_{i} \) represent the minimum SINR requirement of the \( i \)-th IT, then \( C1 \) denotes a set of QoS constraints for \( K_i \) ITs. \( P_{e}^{\text{min}} \) in \( C2 \) represents the minimum energy transmission requirements by the active ETs while \( P_{z}^{\text{idle}} \) in \( C3 \) is the requirements of minimum energy harvested from the surroundings by the idle ETs.
C4 indicates that the total transmit power of each RRH is constrained by its power budget. C5 denotes that the total transmit power should not exceed the maximum transmit power allowance $P_{n}^{\text{T max}}$ at the $n$-th RRH. C6 denotes the fronthaul link capacity restrictions for the individual RRHs. C7 specifies the constraint for the total power supplied by the grid to the RRHs, where $P_{CP}^{\text{circuit}}$ and $P_{CP}^{\text{max}}$ are the hardware circuit power consumption and the maximum power provision by grid at the CP, respectively. C8 and C9 are the non-negative optimization variables.

### 4.3.2 Resource Management Algorithm Design

The optimization problem in (4.7) is non-deterministic polynomial-time (NP)-hard due to the non-convexity of the constraint C1, the $\ell_0$-norm in the first term of the objective function and $C_{fronthaul}^n$ in the constraint C6. By using convex relaxation technique [11], the $\ell_0$-norm term in the objective function of (4.7) and C6 can be approximated by their weighted $\ell_1$-norm, respectively, as follows

\[
\mathcal{G}^{[\text{coop}]} 
\approx \sum_{i \in \mathcal{L}_i} \sum_{i \in \mathcal{L}_i} \| \xi_{ni} \| w_{ni} \| 2 \|_1 + \sum_{e \in \mathcal{L}_e} \sum_{e \in \mathcal{L}_e} \| \xi_{ne} \| w_{ne} \| 2 \|_1 \\
+ \sum_{n \in \mathcal{L}_b} \left( \sum_{i \in \mathcal{L}_i} \xi_{ni} \| w_{ni} \| 2 \right) + \sum_{n \in \mathcal{L}_b} \left( \sum_{e \in \mathcal{L}_e} \kappa_{ne} \| v_{ne} \| 2 \right) \\
= \sum_{n \in \mathcal{L}_b} \left( \sum_{i \in \mathcal{L}_i} \xi_{ni} \| w_{ni} \| 2 \right) + \sum_{n \in \mathcal{L}_b} \left( \sum_{e \in \mathcal{L}_e} \kappa_{ne} \| v_{ne} \| 2 \right),
\]

\[
C_{fronthaul}^n = \sum_{i \in \mathcal{L}_i} \| w_{ni} \| 2 \|_0 R_i \approx \sum_{i \in \mathcal{L}_i} \| \xi_{ni} \| w_{ni} \| 2 \|_1 R_i \\
= \sum_{i \in \mathcal{L}_i} \xi_{ni} \| w_{ni} \| 2 R_i = \sum_{i \in \mathcal{L}_i} \xi_{ni} \text{tr}(w_{i} w_{i}^H D_n) R_i,
\]

where $D_n \triangleq \text{Bdiag}(0_1, \ldots, 0_{i}, \ldots, 0_{N}) \preceq 0, \forall n \in \mathcal{L}_b$ is a block diagonal matrix, $0_1$ is an $M \times M$ matrix with all-zero elements and $I_n$ is an $M \times M$ identity matrix. $\xi_{ni} \geq 0$ and $\kappa_{ne} \geq 0$, respectively, are the weighting factors associated with the $n$-th RRH and the $i$-th IT/the $e$-th active ET. It has been argued in [9] that weights
could counteract the influence of the signal magnitude on the $\ell_1$ norm surrogate to $\ell_0$ norm, as $\ell_0$ norm simply counts the number of nonzero elements of a vector and is not sensitive to their actual values.

Thus, this chapter introduces a reweighted $\ell_1$-norm method for SWIPT in Algorithm 3, where the weights are set to be inversely proportional to the true signal magnitude in steps 4 and 5. Since obtaining a valid set of weights depends on knowing the optimal beamformers, i.e., $w_{ni}^*, \forall n, \forall i$, the proposed Algorithm 3 alternates between computing the beamformers and redefining the weights by first solving the optimization problem (4.10) in step 3 and then updating the weights in steps 4 and 5. In particular, the RRH transmitting with low transmit power to a particular receiving terminal in the $t$-th iteration results in a large weighting factor, which will force further reduction in the transmit power of the same RRH in the $(t+1)$-th iteration until the solution sparsity is attained. Consequently, the cooperative links between the RRHs and the active receiving terminals are iteratively removed on the basis of the power budgets and fronthaul link capacity restrictions at the individual RRHs.

Algorithm 3 Reweighted $\ell_1$-norm method for SWIPT

1: Initialize: constant $\mu \to 0$, iteration count $t = 0$, weighting factor $\xi_{ni}(t) = 1$, $\kappa_{ne}(t) = 1$, maximum number of iterations $t_{max}$, $\hat{R}_i(t) = \log_2(1 + \gamma_i)$.
2: while $\xi_{ni}$ and $\kappa_{ne}$ are not converged or $t \neq t_{max}$ do
3: Find the optimal beamformers $W_i^*(t)$ and $V_e^*(t)$ by solving (4.10);
4: Update the weight factor $\xi_{ni}(t + 1)$ as follows,
   $$\xi_{ni}(t + 1) = \frac{1}{\text{tr}(W_i^*(t)D_n) + \mu}, \forall n \in L_b, i \in L_i;$$
5: Update the weight factor $\kappa_{ne}(t + 1)$ as follows,
   $$\kappa_{ne}(t + 1) = \frac{1}{\text{tr}(V_e^*(t)D_n) + \mu}, \forall n \in L_b, e \in L_e;$$
6: Calculate the achievable rate $R_i(t)$ as follows,
   $$R_i(t) = \log_2[1 + \frac{\text{tr}(H_iW_i^*(t))}{\sum_{j \in L_i, j \neq i} \text{tr}(H_iW_j^*(t)) + \sum_{e \in L_e} \text{tr}(H_iV_e^*(t)) + \sigma_i^2];$$
7: Update $\hat{R}_i(t + 1) = R_i(t)$;
8: Increment the iteration number $t = t + 1$;
9: end while

Let us set $H_i = h_ih_i^H$, $G_e = g_eg_e^H$, $F_z = f_zf_z^H$ and define the unit-rank semidef-
finite matrices as $W_i = w_iw_i^H$ and $V_e = v_ev_e^H$. Then the second term of objective function of problem (4.7) can be expressed as

$$\sum_{n \in \mathcal{L}_b} P_n^{[T_x]} = \sum_{i \in \mathcal{L}_i} \sum_{n \in \mathcal{L}_b} \text{tr}(w_iw_i^H D_n) + \sum_{e \in \mathcal{L}_e, n \in \mathcal{L}_b} \text{tr}(v_ev_e^H D_n) = \sum_{i \in \mathcal{L}_i} \text{tr}(W_i) + \sum_{e \in \mathcal{L}_e} \text{tr}(V_e).$$

The original optimization problem in (4.7) can be transformed to a semidefinite programming (SDP) problem after relaxing the unit-rank constraints of $\text{rank}(W_i) = 1$ and $\text{rank}(V_e) \leq 1$, as

$$\begin{align*}
\min_{W_i, V_e, \chi} & \quad \alpha \sum_{n \in \mathcal{L}_b} \left( \sum_{i \in \mathcal{L}_i} \xi_{ni} \text{tr}(W_i D_n) + \sum_{e \in \mathcal{L}_e} \kappa_{ne} \text{tr}(V_e D_n) \right) \\
& \quad + \beta \left( \sum_{i \in \mathcal{L}_i} \text{tr}(W_i) + \sum_{e \in \mathcal{L}_e} \text{tr}(V_e) \right) + \chi, \\
\text{s.t.} & \quad \text{C1 : } \text{tr}(H_i W_i) \geq \gamma_i \sum_{j \in \mathcal{L}_i, j \neq i} \text{tr}(H_i W_j) \\
& \quad \quad + \gamma_i \sum_{e \in \mathcal{L}_e} \text{tr}(H_i V_e) + \gamma \sigma_i^2, \quad \forall i \in \mathcal{L}_i, \\
& \quad \text{C2 : } \text{tr}(G_e V_e) + \sum_{j \in \mathcal{L}_e, j \neq e} \text{tr}(G_e V_j) \\
& \quad \quad + \sum_{i \in \mathcal{L}_i} \text{tr}(G_e W_i) \geq P_e^{[\text{min}] \eta^{-1}}, \quad \forall e \in \mathcal{L}_e, \\
& \quad \text{C3 : } \sum_{i \in \mathcal{L}_i} \text{tr}(F_z W_i) + \sum_{e \in \mathcal{L}_e} \text{tr}(F_z V_e) \geq P_z^{[\text{idle}] \eta^{-1}}, \quad \forall z \in \mathcal{L}_e^{[\text{idle}]}, \\
& \quad \text{C4 : } \sum_{i \in \mathcal{L}_i} \text{tr}(W_i D_n) + \sum_{e \in \mathcal{L}_e} \text{tr}(V_e D_n) \leq [E_n - S_n] \\
& \quad \quad + B_n^{[\text{ahead}]} + B_n^{[\text{real}]} - P_n^{[\text{circuit}]}, \quad \forall n \in \mathcal{L}_b, \\
& \quad \text{C5 : } \sum_{i \in \mathcal{L}_i} \text{tr}(W_i D_n) + \sum_{e \in \mathcal{L}_e} \text{tr}(V_e D_n) \leq P_n^{[\text{max}]}, \quad \forall n \in \mathcal{L}_b, \\
& \quad \text{C6 : } \sum_{i \in \mathcal{L}_i} \xi_{ni} \text{tr}(W_i D_n) R_i \leq C_n^{[\text{b-limit}]}, \quad \forall n \in \mathcal{L}_b, \\
& \quad \text{C7 : } B_n^{[\text{ahead}]} + \sum_{n \in \mathcal{L}_b} B_n^{[\text{real}]} \leq P_n^{[\text{max}]} - P_n^{[\text{circuit}]}, \\
& \quad \text{C8 : } B_n^{[\text{real}]} \geq 0, \quad \forall n \in \mathcal{L}_b, \\
& \quad \text{C9 : } S_n \geq 0, \quad \forall n \in \mathcal{L}_b, \\
& \quad \text{C10 : } \xi B_n^{[\text{real}]} \leq \chi, \quad \forall n \in \mathcal{L}_b, \\
& \quad \text{C11 : } W_i \geq 0, \quad \forall i \in \mathcal{L}_i, \\
& \quad \text{C12 : } V_e \geq 0, \quad \forall e \in \mathcal{L}_e.
\end{align*}$$
4.4 Strategy 2: DRRHC with Overall Energy Purchase Minimization

4.4.1 Problem Formulation

Second strategy proposes a different approach for energy trading optimization by jointly minimizing the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, the RRHs’ total transmit power and the overall real-time energy purchase from the grid, under the constraints of satisfying the QoS/energy transmission requirements of the ITs/ETs, respectively. The proposed strategy 2 can be formulated as

\[
\min_{w_n, v_n, B_n^{[\text{real}]}} \quad \alpha P_{[\text{coop}]}^{[\text{real}]} + \beta \sum_{n \in \mathcal{L}_b} P_n^{[\text{Tx}]} + \zeta \sum_{n \in \mathcal{L}_b} \left\{ B_n^{[\text{real}]} \right\}
\]

s.t. \( C_1 - C_9 \) in (4.7).

where \( \alpha \geq 0 \) is the maximum power cost in the fronthaul due to the transportation of an active receiving terminal’s data from the CP to a serving RRH. The weighting coefficients \( \beta \geq 0 \) and \( \zeta \geq 0 \) model the degrees of CP’s emphasis on minimizing the RRHs’ total transmit power and the overall real-time energy-purchase from grid, respectively.

4.4.2 Resource Management Algorithm Design

Following the similar SDR approach as in the strategy 1, the problem of strategy 2 in (4.11) can be transformed as

\[
\min_{W_i, V_e, B_n^{[\text{real}]}} \quad \alpha \sum_{n \in \mathcal{L}_b} \left( \sum_{i \in \mathcal{L}_i} \xi_{ni} \text{tr}(W_i D_n) + \sum_{e \in \mathcal{L}_e} \kappa_{ne} \text{tr}(V_e D_n) \right)
\]

\[
+ \beta \left( \sum_{i \in \mathcal{L}_i} \text{tr}(W_i) + \sum_{e \in \mathcal{L}_e} \text{tr}(V_e) \right) + \zeta \sum_{n \in \mathcal{L}_b} \left\{ B_n^{[\text{real}]} \right\}
\]

s.t. \( C_1 - C_9, C_{11} - C_{12} \) in (4.10).
Note that, if the obtained solutions $W^*_i$ and $V^*_e$ are rank-one, the problems (4.10) and (4.12) yield same optimal solutions as problems (4.7) and (4.11), respectively.

**Lemma 1:** The optimal solutions to the problems (4.10) and (4.12) satisfy

$$\text{rank}(W^*_i) = 1 \text{ and } \text{rank}(V^*_e) \leq 1 \text{ with probability one.}$$

**Proof:** Please refer to the Appendix A.

### 4.5 Simulation Results

As shown in Figure 4.2, the simulation considers a SWIPT C-RAN consists of 3 neighbouring 8-antennas RRHs, located 500m away from each other. Please note that this chapter formulates more realistic scenarios where RRHs are constrained with limited fronthaul capacities. In this simulation, $C_{n}^{[\text{bit-limit}]} = 40 \text{ bit/s/Hz, } \forall n \in \mathcal{L}$ has been chosen to study the impact of fronthaul capacity constraints in the proposed problem formulations. 6 ITs and 6 ETs are randomly generated in the network and the weight factor of energy serving area for ETs is $\varphi_{nm} = 0.2$. The renewable energy generation at each RRH is assumed to be $E_1 = 1.5 \text{ W, } E_2 = 0.2 \text{ W and } E_3 = 0.05 \text{ W, respectively, at price of } \pi^{[\text{renew}]} = £0.02/\text{W.}$. It is
further assumed that the RRH has purchased $B_1^{[\text{ahead}]} = B_2^{[\text{ahead}]} = B_3^{[\text{ahead}]} = 0.7$ W from the day-ahead market at price of $\pi^{[\text{ahead}]} = £0.07/W$ and can purchase additional energy from real-time market at price of $\pi^{[\text{real}]} = £0.15/W$ and sell excessive energy back to the grid at price of $\pi^{[\text{sell}]} = £0.05/W$. Besides, the channel vectors $\mathbf{h}_i$, $\mathbf{g}_e$ and $\mathbf{f}_\zeta$ are assumed to be independently distributed and a correlated channel model $\mathbf{h}_{ni} = \mathbf{R}^{1/2}\mathbf{h}_n$ is adopted [57], where $\mathbf{h}_n \sim \mathbb{C}^{M \times 1}$, $\mathbf{R} \in \mathbb{C}^{M \times M}$ is the spatial covariance matrix and its $(m,n)$-th element is given by $G_a L_p \sigma_f^2 e^{-0.5 \left( \frac{10 d_i}{\eta} \right)^2 \left( \delta \lambda \sin \theta \right)} e^{-2 \left( \frac{\pi \delta \lambda}{\lambda} (n-m) \cos \theta \right)^2}$, where antenna gain $G_a = 15$ dBi, $L_p (\text{dB}) = 125.2 + 36.3 \log_{10}(d)$ is the path loss model over a distance of $d$ km, $\sigma_f^2$ is the variance of complex Gaussian fading coefficient, log-normal shadowing standard deviation $\sigma_s = 8$ dB, antenna spacing $\delta = \lambda/2$, angular offset standard deviation $\sigma = 2^\circ$ and $\theta$ is the estimated angle of departure. The channel bandwidth, noise figure at receiving terminals and noise power spectral density are set to be 20 MHz, 5 dB and $-174$ dBm/Hz, respectively. Besides, the parameters for optimization constraints are set to be $P_{\text{CP}}^{[\text{circuit}]} = 40$ dBm, $P_{\text{CP}}^{[\text{max}]} = 50$ dBm, $P_{n}^{[\text{circuit}]} = 30$ dBm, $P_{n}^{[\text{Tmax}]} = 46$ dBm, $P_{e}^{[\text{min}]} = -60$ dBm, $P_{\zeta}^{[\text{idle}]} = -90$ dBm and $\eta = 0.5$, respectively. The simulation results are efficiently obtained via CVX [108] and are averaged over 200 independent channel realizations. The list of parameters used in this simulation are summarized in Table 4.1. Note that in simulations, the power in the objective function and the constraints of the optimization problems in (4.7) and (4.11), has been normalized with respect to $\alpha$, i.e., $\alpha = 1$. Further in the simulations, the same preference on the second and the third terms of the optimization problems in (4.7) and (4.11) is given by setting equal values for the weighting coefficients $\beta$ and $\zeta$, i.e., $\beta = \zeta = 1$. Note that five strategies are employed in this chapter as comparison group and identical constraints are applied to all of the strategies for fair comparison. They are, respectively, 1. the strategy in [10] that jointly optimizes the fronthaul capacity via partial cooperation and the total transmit power; 2. the joint minimization of cooperative energy trading and full cooperation among RRHs in [7]; 3. the proposed strategy 1 without ET authorization algorithm; 4. a special case of the proposed strategy 1 by setting $(\alpha = 0, \beta = \zeta = 1)$ for jointly optimizing
### 4.5. Simulation Results

Table 4.1: Simulation parameters for Chapter 4.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of RRHs ($N$)</td>
<td>3</td>
</tr>
<tr>
<td>Number of antennas per RRH ($M$)</td>
<td>8</td>
</tr>
<tr>
<td>Number of the ETs ($K_{e} + K_{z[^{idle}]}$)</td>
<td>6</td>
</tr>
<tr>
<td>Number of ITs ($K_{i}$)</td>
<td>6</td>
</tr>
<tr>
<td>Amount of renewable energy generated at the $n$-th RRH</td>
<td>$E_{1} = 1.5W$, $E_{2} = 0.2W$</td>
</tr>
<tr>
<td></td>
<td>$E_{3} = 0.05W$</td>
</tr>
<tr>
<td>Amount of energy purchased from the day-ahead market for the $n$-th RRH</td>
<td>$B_{1[^{ahead}]} = B_{2[^{ahead}]} = B_{3[^{ahead}]} = 0.7W$</td>
</tr>
<tr>
<td>Price of generating per unit renewable energy ($\pi[^{renew}]$)</td>
<td>£0.02 per unit energy</td>
</tr>
<tr>
<td>Price of purchasing per unit energy from the day-ahead market ($\pi[^{ahead}]$)</td>
<td>£0.07 per unit energy</td>
</tr>
<tr>
<td>Price of purchasing per unit energy from the real-time market ($\pi[^{real}]$)</td>
<td>£0.15 per unit energy</td>
</tr>
<tr>
<td>Price of selling per unit energy to the grid ($\pi[^{sell}]$)</td>
<td>£0.05 per unit energy</td>
</tr>
<tr>
<td>Distance between two adjacent RRHs ($D$)</td>
<td>500 m</td>
</tr>
<tr>
<td>Channel bandwidth’s wide</td>
<td>20 MHz</td>
</tr>
<tr>
<td>Circuit power consumption at the CP ($P_{CP[^{circuit}]max}$)</td>
<td>40 dBm</td>
</tr>
<tr>
<td>Maximum power provision at the CP ($P_{CP[^{max}]max}$)</td>
<td>50 dBm</td>
</tr>
<tr>
<td>Circuit power consumption at the $n$-th RRH ($P_{n[^{circuit}]max}$)</td>
<td>30 dBm</td>
</tr>
<tr>
<td>Maximum transmit power allowance ($P_{n[^{max}]}$)</td>
<td>46 dBm</td>
</tr>
<tr>
<td>Minimum energy required by the active ETs ($P_{e[^{min}]}$)</td>
<td>$-60$ dBm</td>
</tr>
<tr>
<td>Minimum energy harvested by the idle ETs ($P_{z[^{idle}]}$)</td>
<td>$-90$ dBm</td>
</tr>
<tr>
<td>Fronthaul capacity limit at the $n$-th RRH ($C_{n[^{b-limit}]max}$)</td>
<td>40 bits/s/Hz</td>
</tr>
<tr>
<td>Energy harvesting efficiency ratio ($\eta$)</td>
<td>0.5</td>
</tr>
<tr>
<td>Weight factor of hexagonal coverage area ($\wp_{nm}$)</td>
<td>0.2</td>
</tr>
<tr>
<td>Array antenna gain ($G_{a}$)</td>
<td>15 dBi</td>
</tr>
<tr>
<td>Noise power spectral density</td>
<td>$-174$ dBm/Hz</td>
</tr>
<tr>
<td>Noise figure at receiving terminals</td>
<td>5 dB</td>
</tr>
<tr>
<td>Path loss model over a distance of $d$ km</td>
<td>$125.2 + 36.3 \log_{10}(d)$</td>
</tr>
<tr>
<td>Angular offset standard deviation ($\sigma$)</td>
<td>2°</td>
</tr>
<tr>
<td>Log-normal shadowing standard deviation ($\sigma_{s}$)</td>
<td>8 dB</td>
</tr>
<tr>
<td>Spacing between two adjacent antenna elements ($\delta$)</td>
<td>$\lambda/2$</td>
</tr>
<tr>
<td>Simulation results are averaged over a number of independent channel realizations</td>
<td>200</td>
</tr>
</tbody>
</table>
the full cooperation and the energy trading with the grid, and 5. a special case of the proposed strategy 1 by setting \((\alpha = 1, \beta = 0, \zeta = 1)\) for jointly optimizing the fronthaul power consumption via partial cooperation and the energy trading with the grid.

The comparison of total energy cost of the RRH for different strategies is presented in Figure 4.3. One can conclude that in terms of total energy cost reduction, overwhelming performance gain can be achieved by both of the proposed joint cooperative energy trading strategies as compared to the baseline strategy in [10] that separately designs the partial cooperation and energy trading. The strategy 2 has the lowest total energy cost in terms of achieving higher SINR targets and closely follows strategy 1\((\alpha = \beta = \zeta = 1)\) and 1\((\alpha = 1, \beta = 0, \zeta = 1)\) at low and medium SINR requirements. It is noticeable that both of the proposed strategies outperform the strategy in [7] in the medium and high target SINR range since full cooperation in [7] may be infeasible for medium and high target SINR due to fronthaul capacity restrictions. In the simulation, the fronthaul capacity limit for all the RRHs has

Figure 4.3: Total energy cost versus various target SINR for different strategies.
been restricted to $C_n^{[\text{b-limit}]} = 40 \text{ bits/s/Hz}, \forall n \in \mathcal{L}_b$. For example, to satisfy 25 dB SINR requirement of all the ITs in the full cooperation scheme, i.e., $\text{SINR}_{i}^{[\text{IT}]} = 25$ dB, $\forall i \in \mathcal{L}_i$, the fronthaul capacity needed at each of the fronthaul links is at least 49.8288 bits/s/Hz, i.e., $(\log_2(1 + \text{SINR}_{i}^{[\text{IT}]}) \times 6 \text{ ITs} = (8.3048 \times 6) \text{ bits/s/Hz} = 49.8288 \text{ bits/s/Hz}$. Therefore, with $C_n^{[\text{b-limit}]} = 40 \text{ bits/s/Hz}$, only $4.816 \sim 4 \text{ ITs}$ can be served in a time at each of the RRHs. Hence, full cooperation scheme may lead to infeasible solutions in practical scenarios.

![Figure 4.4: Total transmit power versus various target SINR for different strategies.](image)

The comparison of the total transmit power versus various SINR targets for different strategies is illustrated in Figure 4.4. It can be observed from the figure that a significant performance gap exists between the proposed strategies 1, 2 that embedded with ET authorization algorithm as well as the proposed strategy 1(without ET authorization algorithm); and the strategies in [10], [7] that have no implementation of ET authorization algorithm. As expected, the strategy 1($\alpha = 0, \beta = \zeta = 1$) that enable full cooperation in C-RAN, consumes lower transmit power as compared to their counterparts up to medium SINR range and then become infeasible
4.5. Simulation Results

due to fronthaul capacity restrictions. Please note that at low to medium SINR requirements, the full cooperation scheme proposed in [7] consumes the highest total transmit power due to its proposed problem formulation that only minimize energy trading without jointly minimize both energy trading and total transmit power. Then, above the 20 dB of SINR requirements, the results become infeasible due to fronthaul capacity restrictions

![Graph showing transmit power variation of RRHs using reweighted ℓ₁-norm method proposed in Algorithm 3 for serving the 3rd IT at γ = 20dB.](image)

**Figure 4.5:** Transmit power variation of RRHs using reweighted ℓ₁-norm method proposed in Algorithm 3 for serving the 3rd IT at γ = 20dB.

Transmit power variation of the individual RRHs using reweighted ℓ₁-norm method proposed in Algorithm 3 for serving the 3rd IT for different strategies at target SINR of γ = 20 dB is presented in Figure 4.5. One can conclude that for the proposed strategies 1 and 2 that apply sparse beamforming for partial cooperation, the transmit power of all the RRHs converge within 12 iterations. In addition, it is illustrated by the figure that only RRH 2 is participating in serving the 3rd IT while RRH 1 and RRH 3 release their cooperative links by iteratively forcing its transmit power close to zero. Whereas, for the full cooperation, i.e., the strategy 1 (α = 0, β = ζ = 1), all the cooperation links are preserved for the 3rd IT.
Figure 4.6: Clustering behaviour of RRH 3 at $\gamma = 20$dB target SINR.

Figure 4.6 illustrates the clustering behaviour of RRH 3 which is in the shortage of power, for different strategies at $\gamma = 20$dB target SINR. It can be observed that for the proposed Strategy 1($\alpha = 1, \beta = 0, \zeta = 1$), Strategy 1($\alpha = \beta = \zeta = 1$) and Strategy 2, only the cooperative links between RRH 3 and the 5th, the 6th ITs are preserved while the transmit power from RRH 3 to the other ITs are dropped close to zero due to its low power budget and fronthaul capacity restriction. Meanwhile, the strategies with full cooperation retain all the joint transmission links between RRH 3 and the ITs.

Figure 4.7 presents in details the comparison of the optimal energy trading for the proposed strategy 1 and 2 at target SINR of $\gamma = 30$ dB. It is noticeable that even though both of the proposed strategies have similar performance in terms of total energy cost of the RRH at $\gamma = 30$ dB, the proposed strategy 1 tends to purchase equal amount of energy from real-time market for individual RRHs, as a result of minimizing the maximum real-time energy-purchase request among the RRHs. Whereas for the proposed strategy 2, all the RRHs utilize all amount of energy without selling back to the grid.
4.5. Simulation Results

Figure 4.7: Optimal energy trading for proposed strategies at $\gamma = 30\text{dB}$. 
4.6 Concluding Remarks

This chapter proposes two joint real-time resource management and energy trading strategies based on sparse beamforming technique in downlink green C-RAN with SWIPT, taking into account the individual fronthaul capacity restrictions, to strike an optimum balance between the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, RRHs’ total transmit power and their maximum or overall energy purchased from the real-time market. To further improve the energy efficiency, an iterative ET authorization algorithm is proposed to design energy beamformers only for the ETs located within the energy serving area of RRHs. By employing the reweighted $\ell_1$-norm approximation for $\ell_0$-norm and SDR, the solution sparsity to the original non-convex optimization problems in (4.7) and (4.11) can be obtained. Simulation results confirm that both of the proposed strategies outperform two other recently proposed schemes in terms of improving the energy efficiency and reducing total energy cost of the RRH in a realistic C-RAN scenario.
Chapter 5

Combinatorial Multi-Armed Bandit Approach for Proactive Energy Management in Green C-RAN

5.1 Introduction

This chapter further extends the previous works to a learning-based practical approach and assume that the centralized cloud computing processor (CP) has no initial knowledge of forthcoming power budget and energy consumption at the individual remote radio heads (RRHs). Two novel iterative algorithms based on combinatorial multi-armed bandit (CMAB) approach, namely, Forward CMAB (ForCMAB) energy trading and Reverse CMAB (RevCMAB) energy trading are introduced to search for the optimal set of energy packages in ascending and descending order of package sizes, respectively. The aim of the proposed strategies is to find the set of optimal sizes of the energy packages to be purchased from the day-ahead market by observing the instantaneous energy demand and learning from the behaviour of cooperative energy trading, so that the total cost of the network operator can be minimized.

5.1.1 Organization

This chapter follows the same system model and problem formulation that have been proposed for Strategy 2: Dynamic RRH-centric Clustering (DRRHC) with
5.2 DRRHC with Overall Energy Purchase Minimization

Overall Energy Purchase Minimization in section 4.4, Chapter 4. For the convenience of reader, the reweighted \( \ell_1 \)-norm method for simultaneous wireless information and power transfer (SWIPT) algorithm proposed in Algorithm 3 and the Strategy 2 that has been transformed in numerically tractable form proposed in problem (4.12), both from Chapter 4, are attached in section 5.2 in this chapter. Two CMAB strategies: Forward Combinatorial Multi-Armed Bandit and Reverse Combinatorial Multi-Armed Bandit are proposed in section 5.4 and 5.5, respectively. Numerical simulation results are analyzed in section 5.6. Finally, section 5.7 summarizes this chapter.

5.2 DRRHC with Overall Energy Purchase Minimization

The reweighted \( \ell_1 \)-norm method for SWIPT for sparse beamforming technique that has been developed in Algorithm 3 and the proposed Strategy 2 that has been transformed in numerically tractable form in problem (4.12), Chapter 4, are represented as follows, respectively,

**Algorithm 4 Reweighted \( \ell_1 \)-norm method for SWIPT**

1: **Initialize**: constant \( \mu \to 0 \), iteration count \( t = 0 \), weighting factor \( \xi_{ni}(t) = 1 \), \( \kappa_{ne}(t) = 1 \), maximum number of iterations \( t_{\text{max}} \), \( \hat{R}_i(t) = \log_2(1 + \gamma_i) \).
2: **while** \( \xi_{ni} \) and \( \kappa_{ne} \) are not converged or \( t \neq t_{\text{max}} \) **do**
3: Find the optimal beamformers \( W_i^*(t) \) and \( V_e^*(t) \) by solving (5.1);
4: Update the weight factor \( \xi_{ni}(t + 1) \) as follows,
   \[ \xi_{ni}(t + 1) = \frac{1}{\text{tr}(W_i^*(t)D_n)} + \mu, \quad \forall n \in \mathcal{L}_b, i \in \mathcal{L}_i; \]
5: Update the weight factor \( \kappa_{ne}(t + 1) \) as follows,
   \[ \kappa_{ne}(t + 1) = \frac{1}{\text{tr}(V_e^*(t)D_n)} + \mu, \quad \forall n \in \mathcal{L}_b, e \in \mathcal{L}_e; \]
6: Calculate the achievable rate \( R_i(t) \) as follows,
   \[ R_i(t) = \log_2[1 + \frac{\text{tr}(H_iW_i^*(t))}{\sum_{j \in \mathcal{L}_j, j \neq i} \text{tr}(H_jW_j^*(t)) + \sum_{e \in \mathcal{L}_e} \text{tr}(H_eV_e^*(t)) + \sigma_i^2}]; \]
7: Update \( \hat{R}_i(t + 1) = R_i(t) \);
8: Increment the iteration number \( t = t + 1 \);
9: **end while.**
5.2. DRRHC with Overall Energy Purchase Minimization

\[
\min_{W_i, \ V_e, \ B_n} \left( \sum_{n \in \mathcal{L}_b} \xi_n \text{tr}(W_i D_n) + \sum_{e \in \mathcal{L}_e} \kappa_e \text{tr}(V_e D_n) \right) + \beta \left( \sum_{i \in \mathcal{L}_i} \text{tr}(W_i) + \sum_{e \in \mathcal{L}_e} \text{tr}(V_e) \right) + \xi \sum_{n \in \mathcal{L}_b} \{ B_{n}^{\text{real}} \}
\]

(5.1)

s.t. C1 : \(\text{tr}(H_i W_i) \geq \gamma \sum_{j \in \mathcal{L}_i, j \neq i} \text{tr}(H_i W_j) + \gamma_i \sigma_i^2, \ \forall i \in \mathcal{L}_i,\)
C2 : \(\text{tr}(G_e V_e) + \sum_{j \in \mathcal{L}_j, j \neq e} \text{tr}(G_e V_j) + \sum_{i \in \mathcal{L}_i} \text{tr}(G_e W_i) \geq P_{e}^{\text{min}} \eta^{-1}, \ \forall e \in \mathcal{L}_e,\)
C3 : \(\sum_{i \in \mathcal{L}_i} \text{tr}(F_z W_i) + \sum_{e \in \mathcal{L}_e} \text{tr}(F_z V_e) \geq P_{z}^{\text{idle}} \eta^{-1}, \ \forall z \in \mathcal{L}_e^{\text{idle}},\)
C4 : \(\sum_{i \in \mathcal{L}_i} \text{tr}(W_i D_n) + \sum_{e \in \mathcal{L}_e} \text{tr}(V_e D_n) \leq |E_n - S_n + B_n^{\text{ahead}} + B_n^{\text{real}} - P_n^{\text{circuit}}|, \ \forall n \in \mathcal{L}_b,\)
C5 : \(\sum_{i \in \mathcal{L}_i} \text{tr}(W_i D_n) + \sum_{e \in \mathcal{L}_e} \text{tr}(V_e D_n) \leq P_n^{\text{Tmax}}, \ \forall n \in \mathcal{L}_b,\)
C6 : \(\sum_{i \in \mathcal{L}_i} \xi_n \text{tr}(W_i D_n) \hat{R}_i \leq C_n^{\text{b-limit}}, \ \forall n \in \mathcal{L}_b,\)
C7 : \(\sum_{n \in \mathcal{L}_b} B_n^{\text{ahead}} + \sum_{n \in \mathcal{L}_b} B_n^{\text{real}} \leq P_{CP}^{\text{max}} - P_{CP}^{\text{circuit}},\)
C8 : \(B_n^{\text{real}} \geq 0, \ \forall n \in \mathcal{L}_b,\)
C9 : \(S_n \geq 0, \ \forall n \in \mathcal{L}_b,\)
C10 : \(W_i \succeq 0, \ \forall i \in \mathcal{L}_i,\)
C11 : \(V_e \succeq 0, \ \forall e \in \mathcal{L}_e,\)
5.3 Combinatorial Multi-Armed Bandit for Real-Time Energy Trading

The multi-armed bandit (MAB) problem models a slot machine attempts to maximize the accumulated reward by iteratively optimizing the decisions among a set of arms based on existing knowledge, known as exploitation, while simultaneously acquiring new knowledge by observing the associated reward, known as exploration [17].

This chapter employs an abstract idea of MAB for the CP to learn from the behaviour of the energy trading in green cloud radio access network (C-RAN) iteratively, where each arm corresponds to the size of an energy package per RRH to be purchased by the network operator from the day-ahead market prior to the actual time of energy demand. Therefore, the new responsibility of the CP is to find the set of optimal sizes of the energy packages to be purchased from the day-ahead market without the initial knowledge of forthcoming instantaneous energy demand, in order to minimize the total energy cost of the network operator.

As illustrated in Figure 5.1, this chapter assumes that there is a total number of \( J \) arms, where only \( N \) arms, \( N \subset J \), can be pulled simultaneously. At each trial, the CP chooses \( N \) sizes of energy packages for \( N \) RRHs, which is equivalent to pulling a set of \( N \) arms simultaneously. Then, the CP observes the individual reward for each arm and calculates the aggregated reward. This problem falls in the category of CMAB [16], because multiple arms are pulled simultaneously and the reward for each arm is observed individually.

Let \( \mathcal{A}_t^{\text{[set]}} = \{B_1^{\text{[ahead]}}(t), \cdots, B_N^{\text{[ahead]}}(t)\} \) indicates \( N \) sizes of energy packages to be purchased by the network operator from the day-ahead market at the \( t \)-th trial. The problem is to decide which combination of arms should be pulled at each \( t \)-th trial in order to maximize the individual reward for the \( n \)-th RRH, i.e., \( \mathcal{R}(B_n^{\text{[ahead]}}(t)) \) and, thus, the accumulated reward, i.e., \( \mathcal{R}(\mathcal{A}_t^{\text{[set]}}) \) in a limited number of trials \( T \),
which can be calculated as

\[
\mathcal{R}(B_n^{\text{ahead}}(t)) = B_n^{\text{total}}(0) - B_n^{\text{total}}(t), \quad \forall n \in \mathcal{L}_b, \quad (5.2)
\]

\[
\mathcal{R}(\mathcal{A}_t^{\text{set}}) = \sum_{n \in \mathcal{L}_b} \mathcal{R}(B_n^{\text{ahead}}(t)). \quad (5.3)
\]

\(B_n^{\text{total}}(0)\) and \(B_n^{\text{total}}(t)\) in (5.2) are the total energy cost of the network operator consumed by the \(n\)-th RRH at the initial trial, i.e., \(t = 0\) and at the \(t\)-th trial respectively,
which are given by

\[
B_n^{[\text{total}]}(t) = \pi^{[\text{ahead}]}B_n^{[\text{ahead}]}(t) + \pi^{[\text{real}]}B_n^{[\text{real}]}(t) + \pi^{[\text{renew}]}E_n(t) - \pi^{[\text{sell}]}S_n(t), \quad \forall n \in \mathcal{L}_b.
\]

This chapter assumes a set of index of the sizes of energy packages offered by the grid during the day-ahead market \(e_i^{[\text{total}]} = \{e^1, \ldots, e^J\} \) with \(e^1 < e^2 < \cdots < e^J\) is an arithmetic progression (AP) with common difference of \(\mathcal{E}\). Furthermore, this chapter define package\([\text{size}] = x\mathcal{E}\), where \(x\) is a constant number that has been chosen by the CP.

## 5.4 Strategy 1: Forward Combinatorial Multi-Armed Bandit

In the sequel, this chapter introduces a forward CMAB (ForCMAB) Energy Trading algorithm to find the optimal combination of arms in an ascending order of packages sizes in a given number of trials \(T\), where \(T = t_{\exp} + t_{\max}\) is the total of exploration trials, \(t_{\exp}\) and exploitation trials, \(t_{\max}\).

The main idea of Strategy 1 is presented in the flow chart for ForCMAB Energy Trading in Figure 5.2 and the steps are written in detail in Algorithm 5. Initially, the CP defines all the initial values such as \(A_0^{[\text{set}]} = \{0_1, \ldots, 0_N\}\), exploration count \(t = 0\), exploitation count \(u = 0\), maximum number of trials \(T\). Note that the CP starts the operation with \(A_0^{[\text{set}]} = \{0_1, \ldots, 0_N\}\) to check if the available local renewable energy is sufficient to satisfy the quality of service (QoS) of the energy receiving terminals (ETs) and information receiving terminals (ITs). If satisfied, the CP will decide not to buy any packages from the day-ahead market. In this initial trial the CP run the Algorithm 4, calculates \(B_n^{[\text{total}]}(0)\) and defines the initial individual reward \(\mathcal{R}(B_n^{[\text{ahead}]}(0)) = 0\), accumulated reward \(\mathcal{R}(A_0^{[\text{set}]})) = 0\) and total accumulated reward over \(T \sum_{x=1}^{T} \mathcal{R}(A_x^{[\text{set}]})) = 0\), \(\forall n \in \mathcal{L}_b\). After that the algorithm resumes to the next trial.

If the accumulated reward at current \(t\)-th trial is higher than the previous trial,
5.4. Strategy 1: Forward Combinatorial Multi-Armed Bandit

i.e., $R(\mathcal{A}_t) \geq R(\mathcal{A}_{t-1})$, the algorithm proceeds to the exploration stage. In the exploration stage, if the individual reward for the $n$-th RRH at the current trial is also higher than the previous trial, i.e., $R(B_n^{\text{ahead}}(t)) \geq R(B_n^{\text{ahead}}(t-1)), \forall n \in \mathcal{L}_b$, then the algorithm explores a new combinatorial arms by purchasing higher sizes of energy packages from the day-ahead market. Perhaps this new combinatorial of arms can contribute to a higher accumulated reward than previous trial. On the other hand, if the accumulated reward at the current $t$-th trial is lower than the previous trial, i.e., $R(\mathcal{A}_t) \leq R(\mathcal{A}_{t-1})$, the algorithm stops the exploration stage and decides to purchase the optimal combination of arms in the exploitation stage until the given number of $T$ trials end. In other words, at each trial $t$, the CP decides to purchase $N$ combination of sizes of the energy packages from the day-ahead market for $N$ RRHs based on the individual reward obtained from the current trial $t$ and the previous trial $(t-1)$ and the iterations of CMAB search are continued until the aggregated reward is maximized.
5.4. Strategy 1: Forward Combinatorial Multi-Armed Bandit

R(A_{set}^t) ≥ R(A_{set}^{t+1})

Exploration of new combinatorial arms

if

R(B_{n[ahead]}^{t}) ≥ R(B_{n[ahead]}^{t-1}) & B_{n[ahead]}^{t} = \emptyset

update A_{set}^{t+1}

Yes

Yes

No

No

Start

CP decides to purchase:
A_{set}^{t+1} = \{B_{1[ahead]}^{t+1}, \ldots, B_{N[ahead]}^{t+1}\}

Exploitation

End

B_{n[ahead]}^{t+1} = B_{n[ahead]}^{t} + \text{package size}

Figure 5.2: Flow chart for ForCMAB Energy Trading.
Algorithm 5 \textit{Forward CMAB (ForCMAB) Energy trading}

1: \textbf{Initialize}: $\mathcal{A}_0^{[\text{set}]} = \{0_1, \cdots, 0_N\}$, exploration count $t = 0$, exploitation count $u = 0$, maximum number of trials $T$.
2: Run Algorithm 4;
   \begin{itemize}
   \item CP calculates $B_n^{[\text{total}]}(0)$ and defines the initial individual reward $\mathcal{R}(B_n^{[\text{ahead}]}(0)) = 0$, accumulated reward $\mathcal{R}(\mathcal{A}_0^{[\text{set}]}(0)) = 0$ and total accumulated reward over $T$.
   \end{itemize}
3: \textbf{while } $\mathcal{R}(\mathcal{A}_t^{[\text{set}]}(t)) \geq \mathcal{R}(\mathcal{A}_{t-1}^{[\text{set}]}(t-1))$ \textbf{do}
4: Increment the iteration number $t = t + 1$.
5: Run Algorithm 4
6: \textbf{Exploration} of new combinatorial arms, $\mathcal{A}_t^{[\text{set}]}(t)$ by solving (5.1);
7: CP calculates $B_n^{[\text{total}]}(t)$, $\mathcal{R}(B_n^{[\text{ahead}]}(t))$ and $\mathcal{R}(\mathcal{A}_t^{[\text{set}]}(t))$, \forall $n \in \mathcal{L}$.
8: \textbf{if} the individual reward for the $n$-th RRH $\mathcal{R}(B_n^{[\text{ahead}]}(t)) \geq \mathcal{R}(B_n^{[\text{ahead}]}(t-1))$ and $B_n^{[\text{ahead}]}(t) \neq \mathcal{A}_n$, \forall $n \in \mathcal{L}$.
9: \textbf{then} update $B_n^{[\text{ahead}]}(t+1) = B_n^{[\text{ahead}]}(t) + \text{package}^{[\text{size}]}$;
10: \textbf{else} update $B_n^{[\text{ahead}]}(t+1) = B_n^{[\text{ahead}]}(t)$, \forall $n \in \mathcal{L}$.
11: \textbf{end if}
12: Update $\mathcal{A}_{t+1}^{[\text{set}]} = \{B_1^{[\text{ahead}]}(t+1), \cdots, B_N^{[\text{ahead}]}(t+1)\}$.
13: \textbf{end while}
14: \textbf{Set } $\mathcal{A}_t^{[\text{set}]}(t) = \mathcal{A}_{t+1}^{[\text{set}]}(t) = \{B_1^{[\text{ahead}]}(t+1), \cdots, B_N^{[\text{ahead}]}(t+1)\}$.
15: Update $t_{\text{exp}} = t$
16: \textbf{while } $u \neq T$ \textbf{do}
17: Increment the iteration number $u = t_{\text{exp}} + 1$.
18: \textbf{Exploitation} of the arms with the optimal reward $\mathcal{A}_u^{[\text{set}]} = \mathcal{A}_t^{[\text{set}]}(t)$, run Algorithm 4 and solve (5.1).
19: CP calculates $B_n^{[\text{total}]}(u)$, $\mathcal{R}(B_n^{[\text{ahead}]}(u))$ and $\mathcal{R}(\mathcal{A}_u^{[\text{set}]}(u))$
20: \textbf{end while}
21: Calculate total accumulated reward over $T$;
   $$\sum_{x=1}^{T} \mathcal{R}(\mathcal{A}_x^{[\text{set}]}(x)) = \sum_{t=1}^{t_{\text{exp}}} \mathcal{R}(\mathcal{A}_t^{[\text{set}]}(x)) + \sum_{u=t_{\text{exp}}+1}^{T} \mathcal{R}(\mathcal{A}_u^{[\text{set}]}(x))$$

5.5 \textit{Strategy 2 : Reverse Combinatorial Multi-Armed Bandit}

In contrast to the strategy used in the former algorithm, Strategy 2 introduce a \textit{reverse CMAB (RevCMAB) Energy Trading} algorithm, i.e., Algorithm 6 to find the
optimal combination of the energy packages in descending order of packages sizes to be purchased from the day-ahead market, so that the maximum individual RRH reward can be achieved, and thus, the total energy cost of the network operator is minimized.

The main idea of Strategy 2 is illustrated in Figure 5.3: Flow chart for RevCMAB Energy Trading. In contrast with Strategy 1, the second strategy defines a set of maximum sizes of energy packages offered by the day-ahead market as a first set of energy packages to be purchased for all the RRHs during the initial trial, i.e., $\mathcal{A}_0^{[\text{set}]} = \{\mathcal{E}_1, \ldots, \mathcal{E}_N\}$. In this initial trial the CP runs the Algorithm 4, calculates $B_n^{[\text{total}]}(0)$ and defines the initial individual reward $\mathcal{R}(B_n^{[\text{ahead}]}(0)) = 0$, accumulated reward $\mathcal{R}(\mathcal{A}_0^{[\text{set}]} = 0$ and total accumulated reward over $T \sum_{x=1}^{T} \mathcal{R}(\mathcal{A}_x^{[\text{set}]} = 0$, $\forall n \in \mathcal{L}_b$. Then the algorithm resumes to the next trial.

If the accumulated reward at current $t$-th trial is higher than the previous trial, i.e., $\mathcal{R}(\mathcal{A}_t^{[\text{set}]} \geq \mathcal{R}(\mathcal{A}_{t-1}^{[\text{set}]})$, the algorithm proceeds to the exploration stage. In contrast to the Strategy 1, in the exploration stage of Strategy 2, if the individual reward for the $n$-th RRH at the current trial is also higher than the previous trial, i.e., $\mathcal{R}(B_n^{[\text{ahead}]}(t)) \geq \mathcal{R}(B_n^{[\text{ahead}]}(t-1)), \forall n \in \mathcal{L}_b$, then the algorithm explores a new combinatorial arms by purchasing lower sizes of energy packages from the day-ahead market. Possibly the amounts of the energy required by the active receiving terminals at the individual RRHs are lower than the amounts of energy provided, makes the CP to sell back the excessive energy to the grid with a lower price. Therefore, it is possible that a new set of lower sizes of energy packages generates a higher accumulated reward. On the other hand, if the accumulated reward at the current $t$-th trial is lower than the previous trial, i.e., $\mathcal{R}(\mathcal{A}_t^{[\text{set}]} \leq \mathcal{R}(\mathcal{A}_{t-1}^{[\text{set}]})$, the algorithm stops the exploration stage and decides to purchase the optimal combination of arms in the exploitation stage until the given number of $T$ trials end.
5.5. Strategy 2: Reverse Combinatorial Multi-Armed Bandit

\begin{align*}
R(A[t]) &\geq R(A[t-1]) \\
R(B_n[t]) &\geq R(B_n[t-1]) \quad \text{&} \quad B_n[t] \neq 0
\end{align*}

\begin{align*}
B_n[t+1] & = B_n[t] - \text{package}[\text{size}] \\
B_n[t+1] & = B_n[t]
\end{align*}

Figure 5.3: Flow chart for RevCMAB Energy Trading.
Algorithm 6 Reverse CMAB (RevCMAB) Energy trading

1: **Initialize:** a set of maximum sizes of energy packages offered by the day-ahead market \( \mathcal{E}_0^{[set]} = \{ \mathcal{E}_1^\#, \ldots, \mathcal{E}_N^\# \} \).
2: Run Algorithm 4;
   
   CP calculates \( B_n^{[total]}(0) \) and defines the initial individual reward
   \( \mathcal{R}(B_n^{[ahead]}(0)) = 0 \), accumulated reward \( \mathcal{R}(\mathcal{A}_0^{[set]}) = 0 \) and total accumulated
   reward over \( T \sum_{x=1}^{T} \mathcal{R}(\mathcal{A}_x^{[set]}) = 0 \), \( \forall n \in \mathcal{L}_b \)
3: **while** \( \mathcal{R}(\mathcal{A}_t^{[set]}) \geq \mathcal{R}(\mathcal{A}_t^{[set]}) \) **do**
4:    Increment the iteration number \( t = t + 1 \).
5:    Run Algorithm 4
6:    Exploration of new combinatorial arms, \( \mathcal{A}_i^{[set]} \) by solving (5.1) ;
7:    CP calculates \( B_n^{[total]}(t) \), \( \mathcal{R}(B_n^{[ahead]}(t)) \) and \( \mathcal{R}(\mathcal{A}_i^{[set]}) \),
   \( \forall n \in \mathcal{L}_b \)
8:    **if** the individual reward for the \( n \)-th RRH
   \( \mathcal{R}(B_n^{[ahead]}(t)) \geq \mathcal{R}(B_n^{[ahead]}(t - 1)) \) and
   \( B_n^{[ahead]}(t) \neq 0 \), \( \forall n \in \mathcal{L}_b \)
9:    **then** update \( B_n^{[ahead]}(t + 1) = B_n^{[ahead]}(t) - \text{package}[\text{size}] \),
10:   **else** update \( B_n^{[ahead]}(t + 1) = B_n^{[ahead]}(t) \), \( \forall n \in \mathcal{L}_b \).
11: **end if**
12: Update \( \mathcal{A}_t^{[set]} = \{ B_1^{[ahead]}(t + 1), \ldots, B_n^{[ahead]}(t + 1) \} \).
13: **end while**
14: Set \( \mathcal{A}_t^{[set]} = \mathcal{A}_t^{[set]} = \{ B_1^{[ahead]}(t + 1), \ldots, B_n^{[ahead]}(t + 1) \} \).
15: Update \( t_{exp} = t \)
16: **while** \( u \neq T \) **do**
17:    Increment the iteration number \( u = t_{exp} + 1 \).
18:    **Exploitation** of the arms with the optimal reward \( \mathcal{A}_u^{[set]} = \mathcal{A}_t^{[set]} \), run Algorithm 4 and solve (5.1).
19:    CP calculates \( B_n^{[total]}(u) \), \( \mathcal{R}(B_n^{[ahead]}(u)) \) and \( \mathcal{R}(\mathcal{A}_u^{[set]}) \)
20: **end while**
21: Calculate total accumulated reward over \( T \);
   \( \sum_{x=1}^{T} \mathcal{R}(\mathcal{A}_x^{[set]}) = \sum_{t=1}^{t_{exp}} \mathcal{R}(\mathcal{A}_t^{[set]}) + \sum_{u=t_{exp}+1}^{T} \mathcal{R}(\mathcal{A}_u^{[set]}) \)

5.6 Simulation Results

This simulation section considers a downlink C-RAN consists of 3 adjacent RRHs
SWIPT towards 30 single-antenna ITs and 6 single-antenna ETs. Each RRH is
equipped with 8 antennas and located 500m away from each other, as shown
in Figure 5.4. The renewable energy generation at each RRH is assumed to
Figure 5.4: A Multi-user Downlink SWIPT C-RAN Simulation Topology.

be $E_1 = 1.5$ W, $E_2 = 0.2$ W and $E_3 = 0.05$ W, respectively, at the price of $\pi_{\text{renew}} = £0.02$/W. The network operator has purchased a set of energy packages $\mathcal{A}^{\text{set}} = \{B_1^{\text{ahead}}, B_2^{\text{ahead}}, B_3^{\text{ahead}}\}$ W from the day-ahead market at the price of $\pi_{\text{ahead}} = £0.07$/W. This chapter runs the Algorithm 5 and Algorithm 6 for $T = 24$ trials with $\mathcal{J} = 48$ and $\mathcal{E}^{\text{total}} = \{100, 200, \ldots, 4800\}$ mW with common difference of $\mathcal{C} = 100$ mW. This chapter further assumes that the network operator can purchase additional energy from the real-time market at the price of $\pi_{\text{real}} = £0.15$/W and sell excessive energy back to the grid at the price of $\pi_{\text{sell}} = £0.05$/W. A correlated channel model $h_{ni} = R^{1/2}h_w$ is adopted [57], where $h_w \in \mathbb{C}^{M \times 1}$ are zero mean circularly symmetric complex Gaussian (ZMCSCG) random variables with unit variance, $R \in \mathbb{C}^{M \times M}$ is the spatial covariance matrix and its $(m,n)$-th element is given by $G_aL_p\sigma_f^2e^{-0.5\frac{(\sigma_s\ln10)^2}{10d}}e^{j\frac{2\pi\delta}{\lambda}(n-m}\sin\theta)e^{-2\frac{\pi\delta\sigma}{\lambda}(n-m)\cos\theta}]^2$, where $G_a = 15$dB is antenna gain, $L_p$(dB)$=125.2+36.3\log_{10}(d)$ is the path loss model over a distance of $d$ km, $\sigma_f^2$ is the variance of the complex Gaussian fading coefficient, $\sigma_s = 8$ dB is the log-normal shadowing standard deviation, $\delta = \lambda/2$ is the antenna spacing, $\sigma = 2^\circ$ is the angular offset standard deviation and $\theta$ is the estimated angle of departure. The channel bandwidth, noise figure at receiving
terminals and noise power spectral density are set to be 20 MHz, 5 dB and $-174 \text{ dBm/Hz}$, respectively. Equal weight factor of serving area for ETs is assumed to be $\varphi_{nm} = 0.2$. Besides, the parameters for optimization constraints are set to be $P_{\text{CP}}^{[\text{circuit}]} = 40 \text{ dBm}$, $P_{\text{CP}}^{[\text{max}]} = 50 \text{ dBm}$, $P_{n}^{[\text{circuit}]} = 30 \text{ dBm}$, $P_{n}^{[\text{Tmax}]} = 46 \text{ dBm}$, $C_{n}^{[\text{b-limit}]} = 40 \text{ bits/s/Hz}$, $P_{e}^{[\text{min}]} = -60 \text{ dBm}$, $P_{e}^{[\text{idle}]} = -90 \text{ dBm}$ and $\eta = 0.5$, respectively. The simulation results are efficiently obtained and averaged over 100 independent channel realizations via CVX [108]. The list of parameters used in this simulation are summarized in Table 5.1.

In order to demonstrate the advantages of our proposed strategies, the strategy in [18] and [21] that assume a set of fixed energy packages, i.e., $\mathcal{A}^{[\text{set}]} = \{B_{1}^{[\text{ahead}]} = B_{2}^{[\text{ahead}]} = B_{3}^{[\text{ahead}]}\} = 700 \text{ mW}$, are employed in this chapter as comparison group and identical constraints are applied to all the strategies for fair comparison. Furthermore, this chapter employ different package sizes for the proposed strategies to study the impact of system parameters. They are, respectively, $\text{ForCMAB Energy Trading}$ algorithm with package$^{[\text{size}]} = 200 \text{ mW}$, $\text{ForCMAB Energy Trading}$ algorithm with package$^{[\text{size}]} = 100 \text{ mW}$, and $\text{RevCMAB Energy Trading}$ algorithm with package$^{[\text{size}]} = 200 \text{ mW}$.

Figure 5.5 compares the total energy cost of the network operator versus number of trials for different strategies at $\gamma = 20 \text{ dB}$. One can conclude that conducive to reducing the total energy cost, overwhelming performance gain can be achieved by both of the proposed CMAB strategies after a few number of trials as compared to the strategy proposed in [18] and [21] that assume a fixed set of energy packages $\mathcal{A}^{[\text{set}]}$ over the trials. The performance gap in the first number of trials is due to the exploration in the learning process of our proposed CMAB strategies. As it can be observed from the figure, the learning speed of the $\text{ForCMAB Energy Trading}$ algorithm is much higher than $\text{RevCMAB Energy Trading}$ algorithm for package$^{[\text{size}]} = 200 \text{ mW}$.

The comparison of the total energy cost of the network operator versus various SINR targets for different strategies at the 24-th trial is illustrated in Figure 5.6. It can be observed from the figure that after 24 times of trials, both of our proposed
Table 5.1: Simulation parameters for Chapter 5.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of trials</td>
<td>$T = 24$</td>
</tr>
<tr>
<td>Total number of arms or energy packages ($J$)</td>
<td>48</td>
</tr>
<tr>
<td>A set of index of the sizes of energy packages offered by the grid during the day-ahead market ($E_t^{[\text{total}]}$)</td>
<td>${100, 200, \cdots, 4800}$ mW</td>
</tr>
<tr>
<td>Number of RRHs ($N$)</td>
<td>3</td>
</tr>
<tr>
<td>Number of antennas per RRH ($M$)</td>
<td>8</td>
</tr>
<tr>
<td>Number of the ETs ($K_e + K_e^{[\text{idle}]}$)</td>
<td>6</td>
</tr>
<tr>
<td>Number of ITs ($K_i$)</td>
<td>30</td>
</tr>
<tr>
<td>Amount of renewable energy generated at the $n$-th RRH</td>
<td>$E_1 = 1.5W$, $E_2 = 0.2W$</td>
</tr>
<tr>
<td></td>
<td>$E_3 = 0.05W$</td>
</tr>
<tr>
<td>Price of generating per unit renewable energy ($\pi^{[\text{renew}]}$)</td>
<td>£0.02 per unit energy</td>
</tr>
<tr>
<td>Price of purchasing per unit energy from the day-ahead market ($\pi^{[\text{ahead}]}$)</td>
<td>£0.07 per unit energy</td>
</tr>
<tr>
<td>Price of purchasing per unit energy from the real-time market ($\pi^{[\text{real}]}$)</td>
<td>£0.15 per unit energy</td>
</tr>
<tr>
<td>Price of selling per unit energy to the grid ($\pi^{[\text{sell}]}$)</td>
<td>£0.05 per unit energy</td>
</tr>
<tr>
<td>Distance between two adjacent RRHs ($D$)</td>
<td>500 m</td>
</tr>
<tr>
<td>Channel bandwidth’s wide</td>
<td>20 MHz</td>
</tr>
<tr>
<td>Circuit power consumption at the CP ($P_{\text{CP}}^{[\text{circuit}]}$)</td>
<td>40 dBm</td>
</tr>
<tr>
<td>Maximum power provision at the CP ($P_{\text{CP}}^{[\text{max}]}$)</td>
<td>50 dBm</td>
</tr>
<tr>
<td>Circuit power consumption at the $n$-th RRH ($P_{\text{CP}}^{[\text{circuit}]}_n$)</td>
<td>30 dBm</td>
</tr>
<tr>
<td>Maximum transmit power allowance ($P_n^{[\text{max}]}$)</td>
<td>46 dBm</td>
</tr>
<tr>
<td>Minimum energy required by the active ETs ($P_{e}^{[\text{min}]}$)</td>
<td>$-60$ dBm</td>
</tr>
<tr>
<td>Minimum energy harvested by the idle ETs ($P_{e}^{[\text{idle}]}$)</td>
<td>$-90$ dBm</td>
</tr>
<tr>
<td>Fronthaul capacity limit at the $n$-th RRH ($C_{[\text{b-limit}]}_n$)</td>
<td>40 bits/s/Hz</td>
</tr>
<tr>
<td>Energy harvesting efficiency ratio ($\eta$)</td>
<td>0.5</td>
</tr>
<tr>
<td>Weight factor of hexagonal coverage area ($\phi_{nm}$)</td>
<td>0.2</td>
</tr>
<tr>
<td>Array antenna gain ($G_a$)</td>
<td>15 dBi</td>
</tr>
<tr>
<td>Noise power spectral density</td>
<td>$-174$ dBm/Hz</td>
</tr>
<tr>
<td>Noise figure at receiving terminals</td>
<td>5 dB</td>
</tr>
<tr>
<td>Path loss model over a distance of $d$ km</td>
<td>$125.2 + 36.3\log_{10}(d)$</td>
</tr>
<tr>
<td>Angular offset standard deviation ($\sigma$)</td>
<td>$2^\circ$</td>
</tr>
<tr>
<td>Log-normal shadowing standard deviation ($\sigma_s$)</td>
<td>8 dB</td>
</tr>
<tr>
<td>Spacing between two adjacent antenna elements ($\delta$)</td>
<td>$\lambda/2$</td>
</tr>
<tr>
<td>Simulation results are averaged over a number of independent channel realizations</td>
<td>100</td>
</tr>
</tbody>
</table>
5.6. Simulation Results

Figure 5.5: Total energy cost versus number of trials at $\gamma = 20$dB.

Figure 5.6: Total energy cost versus various target SINR at $T = 24$.

*ForCMAB Energy Trading* and *RevCMAB Energy Trading* algorithms outperform the strategy proposed in [18] and [21] in terms of total energy cost of the network operator. Furthermore, the performance gap increases with the increasing SINR.
5.7 Concluding Remarks

This chapter proposes two CMAB algorithms, namely, ForCMAB Energy Trading and RevCMAB Energy Trading, to observe the instantaneous energy demand and learn from the behaviour of cooperative energy trading in the green C-RAN with requirements.

Figure 5.7 presents in details a set of the optimal energy packages chosen by the CP to be purchased from the day-ahead market at the 24th trial. It is noticeable that instead of using a fixed set of energy packages, both of our proposed strategies purchase a set of optimal energy packages from day-ahead market on the basis of actual energy generation and the energy requirements at the individual RRHs.

In addition, even though both of the proposed strategies have similar performance in terms of total energy cost of the network operator at $\gamma = 20$ dB, the proposed RevCMAB Energy Trading algorithm tends to purchase higher amount of energy packages from the day-ahead market for the individual RRHs.

Figure 5.7: Average set of optimal sizes of the energy packages to be purchased from the day-ahead market decided by the CP at $T = 24$ and $\gamma = 20$dB.
SWIPT. At each trial, the sparse beamforming technique is employed to find the optimal trade-off between the cooperative transmission and the total energy cost of the network operator. Assuming that the RRHs have no initial knowledge of forthcoming energy consumption and renewable energy production in real-time energy trading, the CMAB learning process is employed to search for the optimal set of energy packages to be purchased from the day-ahead market in a limited number of trials, to further reduce the total energy cost of the network operator. If some initial knowledge of forthcoming energy consumption or renewable energy production are available, then the optimal set of energy packages to be purchased from the day-ahead market can be searched in a few trials and the accumulated reward can be maximized. Simulation results confirm that in terms of reducing the total energy cost of the network operator, both proposed strategies outperform two recently proposed strategies without CMAB approach in green C-RAN.
Chapter 6

An Online Learning Approach : A Smart Energy Management

6.1 Introduction

In this chapter, a smart energy management strategy based on the combinatorial multi-armed bandit (CMAB) theory for cloud radio access network (C-RAN), which is powered by a hybrid of grid and renewable energy sources is developed. A combinatorial upper confidence bound (CUCB) algorithm is introduced to maximize the overall rewards, earned as a result of minimizing the cost of energy trading at individual remote radio heads (RRHs) of the C-RAN. Adapting to the dynamic wireless channel conditions, the proposed CUCB algorithm associates a set of optimal energy packages, to be purchased from the day-ahead markets, to a set of RRHs to minimize the total cost of energy purchase from the main power grid by dynamically forming super arms. A super arm is formed on the basis of calculating the instantaneous energy demands at the current time slot, learning from the cooperative energy trading at the previous time slots and adjusting the mean rewards of the individual arms. This chapter further extends the work in chapter 5 as well as [22] in a more general approach and proposes a CUCB strategy for combinatorial generalization of the multi-armed bandit (MAB) problem in the field of joint management of real-time resource allocation and energy trading. Under the assumption that prior knowledge of neither the forthcoming power budget nor the
6.2. An Online Learning Approach for A Smart Real-Time Energy Trading

amount of energy consumption at individual RRHs are available to the centralized cloud computing processor (CP), the aim of the proposed strategy in this chapter is to dynamically determine an optimal set of energy packages for the RRHs to be purchased from the day-ahead market as per wireless channel conditions at the individual time slots, so that the total energy cost of the network operator can be further reduced. In contrast to the cooperative energy trading designs proposed in the previous chapter, this chapter proposes a CUCB-CMAB strategy that will estimate the forthcoming energy demands and select an optimal set of energy packages to be purchased from the day-ahead market for the next time slot based on the observation of instantaneous energy demands at the current time slot and learning from the cooperative energy trading at previous time slots.

6.1.1 Organization

This chapter follows the same system model and problem formulation that have been proposed for the Dynamic RRH-centric Clustering (DRRHC) with Overall Energy Purchase Minimization strategy. Please refer to section 5.2, Chapter 5. The rest of this chapter is organized as follows. In section 6.2, problem formulation for online learning approach and CUCB-CMAB algorithms, namely CMAB for Super Arm Exploration Algorithm and CUCB-CMAB Main Algorithm are proposed. Numerical simulation results are analyzed in section 6.3. Finally, section 6.4 summarizes this chapter.

6.2 An Online Learning Approach for A Smart Real-Time Energy Trading

6.2.1 Problem Formulation for Online Learning Approach

The CP applies CMAB to adapt its energy trading strategies to the intermittent environment in C-RAN by dynamically forming super arms to maximize the accumulated rewards, which is equivalent to minimizing the total cost of the network operator. A super arm is composed of a set of arms and each arm corresponds to the size of an energy package to be purchased for an RRH from the day-ahead market.
6.2. An Online Learning Approach for A Smart Real-Time Energy Trading

prior to the actual time of energy demand.

Let \( J = \{1, \cdots, J\} \) indicate a set of indexes for possible energy packages offered in the day-ahead market by the grid. At each trial, the CP allocates a super arm composed of \( N \) arms, i.e., \( N \) sizes of energies out of \( J \) possible energy packages, to \( N \) RRHs. Since, this is equivalent to choosing simultaneously a set of \( N \) arms from \( J \) possible arms, the involved MAB problem is categorized as the CMAB problem \([16]\). Let \( E_{\text{[total]}} = \{E_1, \cdots, E_J\} \) represent the set of sizes of energy packages offered by the grid in the day-ahead market, where \( E_1 < E_2 < \cdots < E_J \) is an arithmetic progression with a common difference of \( \Delta E \), i.e., \( E_p = E_{p-1} + \Delta E, p \in J \).

Furthermore, let \( A_{\text{[set]}_k} = \{B_1^{\text{[ahead]}(k)}, \cdots, B_N^{\text{[ahead]}(k)}\} \) denote a set of \( N \) energy sizes, i.e., a super arm, to be purchased for \( N \) RRHs by the network operator from the day-ahead market at the \( k \)-th trial. Then, the total energy cost of the network operator incurred by the \( n \)-th RRH at the \( k \)-th trial, i.e., \( B_n^{\text{[total]}(k)} \), can be calculated as

\[
B_n^{\text{[total]}(k)} = \pi^{\text{[ahead]}}B_n^{\text{[ahead]}(k)} + \pi^{\text{[real]}}B_n^{\text{[real]}(k)} + \pi^{\text{[renew]}}E_n(k) - \pi^{\text{[sell]}}S_n(k), \quad \forall n \in L_b.
\] (6.1)

Let further define the individual reward for the \( n \)-th RRH and the overall reward for the super arm at the \( k \)-th trial as \( R(B_n^{\text{[ahead]}(k)}) \) and \( R(A_{\text{[set]}_k}) \), respectively, as follows

\[
R(B_n^{\text{[ahead]}(k)}) = B_n^{\text{[total]}(1)} - B_n^{\text{[total]}(k)}, \forall n \in L_b, \quad (6.2)
\]

\[
R(A_{\text{[set]}_k}) = \sum_{n \in L_b} R(B_n^{\text{[ahead]}(k)}), \quad (6.3)
\]

where \( B_n^{\text{[total]}(1)} \) and \( B_n^{\text{[total]}(k)} \) in (6.2) are the total energy cost of the network operator incurred by the \( n \)-th RRH, respectively, at the initial trial and the \( k \)-th trial of a frame. Let \( \mathcal{K} = \{1, \cdots, K\} \), \( \mathcal{F} = \{1, \cdots, F\} \) and \( \mathcal{T} = \{1, \cdots, T\} \) be respectively associated to the set of indexes of the trials within a frame, the set of indexes of the frames within a time slot and the set of indexes of the time slots.
6.2. An Online Learning Approach for A Smart Real-Time Energy Trading

Then, the sum of the total energy cost of all the RRHs in the \( k \)-th trial of the \( f \)-th frame at time slot \( t \) can be denoted as \( \beta^{[k,f,t]} \). Furthermore, \( \mu^{[k,f,t]}_n = (\mu^{[k,f,t]}_{n,1}, \mu^{[k,f,t]}_{n,2}, \ldots, \mu^{[k,f,t]}_{n,J}) \), where \( \mu^{[k,f,t]}_{n,p}, p \in \mathcal{J} \), is the reward associated to the \( p \)-th energy package in the \( k \)-th trial of the \( f \)-th frame at time slot \( t \), indicate the reward vector for the \( n \)-th RRH.

6.2.2 CUCB-CMAB Algorithms for Online Learning Approach

In the sequel, this section introduces a CUCB-CMAB strategy, illustrated in Figure 6.1 and detailed in Algorithm 7 and Algorithm 8. In the exploration stage within each frame, Algorithm 7 explores new combination of energy packages for the next trial based on the rewards gained at the current and the previous trials. Once a given number of trials are completed, the mean rewards in each frame are estimated for individual arms, i.e., energy packages. The estimated mean rewards are, first, adjusted and averaged over the total number of frames of a time slot, then, averaged again over the total number of past time slots and, finally, used to update the super arm to be exploited in the next time slot, all by the CUCB-CMAB main algorithm, as detailed in Algorithm 8.

![Figure 6.1: Proposed CUCB-CMAB strategy for Energy trading in C-RAN.](image)

Algorithm 7, i.e, \textit{CMAB for Super Arm Exploration Algorithm} selects the super
arm of the next trial $k + 1$ to play based on the rewards of revealed arms of the current and the previous trials, without knowing the forthcoming outcomes.

Algorithm 7 CMAB for Super Arm Exploration Algorithm.

1: For $k = 1 : K$
2: Run Algorithm 4 and solve problem (5.1);
3: CP calculates $B_n^{\text{total}}(k)$ as per (6.1) and $\mathcal{R}(B_n^{\text{ahead}}(k))$ as per (6.2);
4: If $k = 1$
5: then
   $B_n^{\text{ahead}}(k + 1) = B_n^{\text{ahead}}(k) + \Delta b$, \quad $n \in \mathcal{L}_b$.
6: else if the super arm reward of all the RRHs
   $\mathcal{R}(\mathcal{A}_k^{[\text{set}])} \leq \mathcal{R}(\mathcal{A}_{k-1}^{[\text{set}])}$,
7: then
   $B_n^{\text{ahead}}(k + 1) = B_n^{\text{ahead}}(k - 1)$, \quad $\forall n \in \mathcal{L}_b$,
8: else if the individual reward for the $n$-th RRH, $n \in \mathcal{N}$
   $\mathcal{R}(B_n^{\text{ahead}}(k)) \geq \mathcal{R}(B_n^{\text{ahead}}(k - 1))$
   and
   $B_n^{\text{ahead}}(k) \neq \mathcal{E}^f$,
9: then
   $B_n^{\text{ahead}}(k + 1) = B_n^{\text{ahead}}(k) + \Delta b$,
10: else
    $B_n^{\text{ahead}}(k + 1) = B_n^{\text{ahead}}(k)$.
11: end If
12: Calculate total energy cost of all the RRHs, $\beta^{[k.f.t]}$ as
    $\beta^{[k.f.t]} = \sum_{n \in \mathcal{L}_b} B_n^{\text{total}}(k)$.
13: Calculate the energy package index $p$ at all RRHs from
    $p = \frac{B_n^{\text{ahead}}(k)}{\Delta b}$, \quad $n \in \mathcal{L}_b$.
14: Update
    $\mu_n^{[k.f.t]} = \mathcal{R}(B_n^{\text{ahead}}(k))$, \quad $\forall p \in \mathcal{J}$, \quad $n \in \mathcal{L}_b$;
15: Update
    $\mathcal{A}_{k+1}^{[\text{set}]} = \{B_1^{\text{ahead}}(k + 1), \ldots, B_N^{\text{ahead}}(k + 1)\}$;
16: End for

Let $\hat{\mu}_n^{[f,t]} = (\hat{\mu}_n^{[f,t]}_1, \hat{\mu}_n^{[f,t]}_2, \ldots, \hat{\mu}_n^{[f,t]}_j, \ldots)$ and $\tilde{\mu}_n^{[f,t]} = (\tilde{\mu}_n^{[f,t]}_1, \tilde{\mu}_n^{[f,t]}_2, \ldots, \tilde{\mu}_n^{[f,t]}_j, \ldots)$, $\forall n \in \mathcal{L}_b$, $f \in \mathcal{F}$, $t \in \mathcal{I}$ represent the mean reward vector and the adjusted reward vector, respectively. By averaging the adjusted reward vector $\tilde{\mu}_n^{[f,t]}$ over $F$ number of frames and over accumulated number of time slots, an optimal super arm $S^*$ will be selected to be applied in the $(t + 1)$-th time slot as shown in detail in the Algorithm 8, i.e., CUCB-CMAB Main Algorithm.
Algorithm 8 CUCB-CMAB Main Algorithm

1: **Initialize**: Time slot count: \( t = 0 \);
2: **while** \( t \neq T \) **do**
3:  Increment the iteration index \( t = t + 1 \);
4:  **for** \( f = 1 \) : \( F \)
5:  **if** \( t = 1 \) (initial time slot)
6:     **then** Initialize the super arm for the first trial \((k = 1)\) as
7:        \( \mathcal{A}_1^{[\text{set}]} = \{0_1, \cdots, 0_N\} \),
8:     **else**
9:        \( \mathcal{A}_1^{[\text{set}]} = S^* \),
10: **end if**
11: **Exploration Stage**: Run Algorithm 7
12: **Estimation Stage**:
13:   Calculate the mean reward vector for the frame
14:      \( \hat{\mu}_n^{[f, t]} = (\hat{\mu}_{n, 1}^{[f, t]}, \hat{\mu}_{n, 2}^{[f, t]}, \cdots, \hat{\mu}_{n, J}^{[f, t]}) \), where
15:      \( \hat{\mu}_{n, p}^{[f, t]} = \frac{\sum_{k=1}^{K} \mu_{k, n, p}^{[f, t]}}{K} \), \( \forall p \in \mathcal{J}, n \in \mathcal{L}_b \).
16: **Adjustment Stage**:
17:   **if** \( \Psi_p \) (number of times the \( p \)-th arm is played) \( \neq 0 \)
18:      **then**
19:          adjust \( \tilde{\mu}_{n, p}^{[f, t]} = \hat{\mu}_{n, p}^{[f, t]} + \sqrt{\frac{3 \ln K}{2 \Psi_p}} \),
20:      **else**
21:          \( \tilde{\mu}_{n, p}^{[f, t]} = \hat{\mu}_{n, p}^{[f, t]} \), \( \forall p \in \mathcal{J}, n \in \mathcal{L}_b \).
22: **end if**
23: **end for**
24: **Exploitation Stage**:
25:   Average \( \tilde{\mu}_n^{[t]} \) over accumulated number of time slots, as
26:      \( \bar{\mu}_n = \frac{\sum_{t=1}^{T} \tilde{\mu}_n^{[t]}}{T} = [\bar{\mu}_{n, 1}, \bar{\mu}_{n, 2}, \cdots, \bar{\mu}_{n, J}] \), \( n \in \mathcal{L}_b \).
27: For the next time slot: find \( N \) optimum arm indexes as
28:   \( p_n^* = \arg\max_{p} (\bar{\mu}_{n, p}), \quad p \in \mathcal{J}, \quad \forall n \in \mathcal{L}_b \),
29: and the updated super arm as
30:   \( S^* = \Delta \mathcal{E}[p_1^*, p_2^*, \cdots, p_N^*] \).
31: **end while**
6.3 Simulation Results

The simulation considers a downlink C-RAN consists of 3 adjacent RRHs towards 6 single-antenna information receiving terminals (ITs) and 6 single-antenna energy receiving terminals (ETs). Each RRH is equipped with 8 antennas and located 500m away from each other. The performance of the proposed approach is evaluated with $K = 10$ trials per frame, $F = 10$ frames per time slot, $T = 60$ time slots, $J = 20$ energy packages and $\Delta E = 100$ mW, i.e., $\mathcal{E}_k^{[\text{total}]} = \{100, 200, \ldots, 2000\}$ mW. The renewable energy generation at each RRH is assumed to be $E_1 = 1.5$ W, $E_2 = 0.2$ W and $E_3 = 0.05$ W, respectively, at price of $\pi^{[\text{renew}]} = £0.02$/W. The network operator purchases a set of energy packages from the day-ahead market at a price of $\pi^{[\text{ahead}]} = £0.07$/W and from the real-time market at a price of $\pi^{[\text{real}]} = £0.15$/W and sell excessive energy back to the grid at a price of $\pi^{[\text{sell}]} = £0.05$/W. A correlated channel model $h_{ni} = R^{1/2}h_w$ is adopted, where $h_w \in \mathbb{C}^{M \times 1}$ are zero mean circularly symmetric complex Gaussian (ZMCSCG) random variables with unit variance, $R \in \mathbb{C}^{M \times M}$ is the spatial covariance matrix and its $(m,n)$-th element is given by $G_\alpha L_p \sigma^2_F e^{-0.5 \frac{(\sigma_s \ln 10)^2}{10} + 36.3 \log_{10}(d)} e^{-2 \frac{(\pi \delta)}{2} (n-m) \cos \theta} e^{-2 \frac{(\pi \delta)}{2} (n-m) \sin \theta}$, where $G_\alpha = 15$ dBi is antenna gain, $L_p \ (\text{dB}) = 125.2 + 36.3 \log_{10}(d)$ is the path loss model over a distance of $d$ km, $\sigma^2_F$ is the variance of the complex Gaussian fading coefficient, $\sigma_s = 8$ dB is the log-normal shadowing standard deviation, $\delta = \lambda/2$ is the antenna spacing, $\sigma = 2^\circ$ is the angular offset standard deviation and $\theta$ is the estimated angle of departure. The channel bandwidth, noise figure at receiving terminals and noise power spectral density are set to be 20 MHz, 5 dB and $-174 \text{ dBm/Hz}$, respectively. Besides, the parameters for optimization constraints are assumed, unless otherwise stated, to be $P_{\text{CP}}^{[\text{circuit}]} = 40 \text{ dBm}$, $P_{\text{CP}}^{[\text{max}]} = 50 \text{ dBm}$, $P_{n}^{[\text{circuit}]} = 30 \text{ dBm}$, $P_{n}^{[\text{max}]} = 46 \text{ dBm}$, $C_n^{[\text{bit-limit}]} = 30 \text{ bits/s/Hz}$, $\gamma = 20 \text{ dB}$, $P_{e}^{[\text{min}]} = -60 \text{ dBm}$, $P_{e}^{[\text{idle}]} = -90 \text{ dBm}$ and $\eta = 0.5$. The simulation results are efficiently obtained and averaged over 100 independent channel realizations via CVX [108]. The list of parameters used in this simulation are summarized in Table 6.1.

The proposed learning-based approach is compared against the baseline strategy, which does not consider purchasing energy packages from the day-ahead mar-
Table 6.1: Simulation parameters for Chapter 6.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of time slots ( (T) )</td>
<td>60</td>
</tr>
<tr>
<td>Total number of frames per time slot ( (F) )</td>
<td>10</td>
</tr>
<tr>
<td>Total number of trials per frame ( (K) )</td>
<td>10</td>
</tr>
<tr>
<td>Total number of arms or energy packages ( (J) )</td>
<td>20</td>
</tr>
<tr>
<td>A set of index of the sizes of energy packages offered by the grid during the day-ahead market ( (\delta_k^{[\text{total}]} ) )</td>
<td>{100, 200, \ldots, 2000} mW</td>
</tr>
<tr>
<td>Number of RRHs ( (N) )</td>
<td>3</td>
</tr>
<tr>
<td>Number of antennas per RRH ( (M) )</td>
<td>8</td>
</tr>
<tr>
<td>Number of the ETs ( (K_{e} + K_{\text{idle}}^{[e]} ) )</td>
<td>6</td>
</tr>
<tr>
<td>Number of ITs ( (K_{i}) )</td>
<td>6</td>
</tr>
<tr>
<td>Amount of renewable energy generated at the ( n )-th RRH</td>
<td>( E_1 = 1.5W, E_2 = 0.2W, E_3 = 0.05W )</td>
</tr>
<tr>
<td>Price of generating per unit renewable energy ( (\pi^{[\text{renew}]} ) )</td>
<td>\£0.02 per unit energy</td>
</tr>
<tr>
<td>Price of purchasing per unit energy from the day-ahead market ( (\pi^{[\text{ahead}]} ) )</td>
<td>\£0.07 per unit energy</td>
</tr>
<tr>
<td>Price of purchasing per unit energy from the real-time market ( (\pi^{[\text{real}]} ) )</td>
<td>\£0.15 per unit energy</td>
</tr>
<tr>
<td>Price of selling per unit energy to the grid ( (\pi^{[\text{sell}]} ) )</td>
<td>\£0.05 per unit energy</td>
</tr>
<tr>
<td>Distance between two adjacent RRHs ( (D) )</td>
<td>500 m</td>
</tr>
<tr>
<td>Channel bandwidth’s wide ( (C) )</td>
<td>20 MHz</td>
</tr>
<tr>
<td>Circuit power consumption at the CP ( (P_{\text{CP}}^{[\text{circuit}]} ) )</td>
<td>40 dBm</td>
</tr>
<tr>
<td>Maximum power provision at the CP ( (P_{\text{CP}}^{[\text{max}]} ) )</td>
<td>50 dBm</td>
</tr>
<tr>
<td>Circuit power consumption at the ( n )-th RRH ( (P_{n}^{[\text{circuit}]} ) )</td>
<td>30 dBm</td>
</tr>
<tr>
<td>Maximum transmit power allowance ( (P_{n}^{[\text{max}]} ) )</td>
<td>46 dBm</td>
</tr>
<tr>
<td>Minimum energy required by the active ETs ( (P_{e}^{[\text{min}]} ) )</td>
<td>(-60 \text{ dBm})</td>
</tr>
<tr>
<td>Minimum energy harvested by the idle ETs ( (P_{z}^{[\text{idle}]} ) )</td>
<td>(-90 \text{ dBm})</td>
</tr>
<tr>
<td>Fronthaul capacity limit at the ( n )-th RRH ( (C_{n}^{[\text{b-limit}]} ) )</td>
<td>30 bits/s/Hz</td>
</tr>
<tr>
<td>Energy harvesting efficiency ratio ( (\eta) )</td>
<td>0.5</td>
</tr>
<tr>
<td>Weight factor of hexagonal coverage area ( (\phi_{hm}) )</td>
<td>0.2</td>
</tr>
<tr>
<td>Array antenna gain ( (G_{a}) )</td>
<td>15 \text{ dBi}</td>
</tr>
<tr>
<td>Noise power spectral density</td>
<td>(-174 \text{ dBm/Hz})</td>
</tr>
<tr>
<td>Noise figure at receiving terminals</td>
<td>5 dB</td>
</tr>
<tr>
<td>Path loss model over a distance of ( d ) km</td>
<td>( 125.2 + 36.3\log_{10}(d) )</td>
</tr>
<tr>
<td>Angular offset standard deviation ( (\sigma) )</td>
<td>2°</td>
</tr>
<tr>
<td>Log-normal shadowing standard deviation ( (\sigma_{s}) )</td>
<td>8 dB</td>
</tr>
<tr>
<td>Spacing between two adjacent antenna elements ( (\delta) )</td>
<td>( \lambda /2 )</td>
</tr>
<tr>
<td>Simulation results are averaged over a number of independent channel realizations</td>
<td>100</td>
</tr>
</tbody>
</table>
kets, and the strategy proposed in [18] and [21], which assumes a set of fixed energy packages to be purchased from the day-ahead market, i.e., 700mW per active RRH, whilst applying identical settings for the purpose of fair comparisons.

**Figure 6.2:** Normalized total energy cost versus index of time slot.

**Figure 6.3:** Normalized total energy cost within 30 time slots.
6.3. Simulation Results

<table>
<thead>
<tr>
<th>Index of Trial</th>
<th>Super arm chosen by the CP at the exploration stage (mW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>500</td>
</tr>
<tr>
<td>3</td>
<td>1000</td>
</tr>
<tr>
<td>4</td>
<td>1500</td>
</tr>
<tr>
<td>5</td>
<td>RRH 1</td>
</tr>
<tr>
<td>6</td>
<td>RRH 2</td>
</tr>
<tr>
<td>7</td>
<td>RRH 3</td>
</tr>
<tr>
<td>8</td>
<td>RRH 1</td>
</tr>
<tr>
<td>9</td>
<td>RRH 2</td>
</tr>
<tr>
<td>10</td>
<td>RRH 3</td>
</tr>
</tbody>
</table>

(a) Super arm chosen by the CP at the exploration stage versus trial at the 5-th time slot.

<table>
<thead>
<tr>
<th>Index of Time Slot</th>
<th>Optimal super arm chosen by the CP at the exploitation stage (mW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>500</td>
</tr>
<tr>
<td>3</td>
<td>1000</td>
</tr>
<tr>
<td>4</td>
<td>1500</td>
</tr>
<tr>
<td>5</td>
<td>RRH 1</td>
</tr>
<tr>
<td>10</td>
<td>RRH 2</td>
</tr>
<tr>
<td>15</td>
<td>RRH 3</td>
</tr>
<tr>
<td>20</td>
<td>RRH 1</td>
</tr>
<tr>
<td>25</td>
<td>RRH 2</td>
</tr>
<tr>
<td>30</td>
<td>RRH 3</td>
</tr>
<tr>
<td>40</td>
<td>RRH 1</td>
</tr>
<tr>
<td>50</td>
<td>RRH 2</td>
</tr>
<tr>
<td>60</td>
<td>RRH 3</td>
</tr>
</tbody>
</table>

(b) Optimal super arm decided by the CP at the t-th time slot to be exploited at the (t+1)-th time slot of the proposed problem formulation.

Figure 6.4: Selected super arms by the CUCB-CMAB strategy.

An inspection of results in Figure 6.2 and Figure 6.3 confirm that the proposed CUCB-CMAB approach reduces the total energy cost by 43 percent and 11 percent,
in the steady state with respect to the baseline and the scheme used in [18] and [21], respectively. It can also be seen from both of the figures that the proposed approach converges to its steady state after about 15 time slots.

Figure 6.4(a) represents in detail a set of the optimal energy packages chosen by the CP to be purchased from the day-ahead market for each trial at the 5-th time slot. At each trial, the CP explores a new combination of energy packages on the basis of actual energy generation and the energy requirements at the individual RRHs. Figure 6.4(b) illustrates the optimal super arm that has been chosen by the CP at the t-th time slot to be exploited at the (t+1)-th time slot of our proposed problem formulation. Note that at the 15-th time slot and onwards, the CP has decided the identical set of super arms for the RRHs that give the optimum rewards.

The normalized accumulated reward and regret of the C-RAN using different strategies are illustrated in Figure 6.5. The normalized accumulated reward, i.e., $\mathcal{R}^{[acc]}_t$ of the CUCB-CMAB is calculated based on the total energy cost of all the RRHs that can be saved at time slot $t$ as compared to the initial point of CUCB-CMAB or the strategy without learning-based. In contrast, the regret, i.e., $\mathcal{D}_t$ of the
models can be defined as $\mathcal{D}_t = R_{\text{opt}}^{\text{acc}} - R_t^{\text{acc}}$, where $R_{\text{opt}}^{\text{acc}}$ is the optimum reward that can be obtained using our learning based strategy. It can be observed from Figure 6.5 that a significant performance gap exists between the proposed CUCB-CMAB and the baseline scheme as well as the strategy in [18] and [21]. Even though the regret of the CUCB-CMAB strategy is worst at the beginning of the learning process, the regrets start to drop at a great rate with the increasing number of time slots.

6.4 Concluding Remarks

This chapter proposes an online learning approach for a smart energy management strategy based on the CMAB approach for green C-RAN with SWIPT. The CUCB-CMAB algorithms are introduced to adapt to the dynamic wireless channel conditions to further minimize the total energy cost of the network operator by maximizing the accumulated rewards obtained at each iteration. The CP calculates and learns the instantaneous energy demand at the current and previous time slots and decides the optimal set of energy packages to be purchased from the day-ahead market for the forthcoming cooperative energy trading. Our simulation results confirm that the total energy cost can be saved up to 43 percent as compared to the baseline strategy and up to 11 percent as compared to the latest scheme in energy trading without any learning-based approach.
Chapter 7

Conclusions and Future Research

7.1 Thesis Summary

Denser site deployment has been regarded as a key enabling technology to support gigantic increasing mobile data traffic and high data rate communications with ubiquitously guaranteed quality of service (QoS) for next generation wireless communication networks [1]. However, the significant inter-cell interference (ICI) may limit the performance of the system. Cloud radio access network (C-RAN) has illustrated its considerable advantages in ICI mitigation as well as reducing both of the capital expenditure (CAPEX) and the operating expense (OPEX) of the network operator. In a C-RAN architecture, the conventional base stations (BSs) are physically detached into two parts: baseband processing units (BBUs) that are grouped into a BBU pool, i.e., a centralized cloud computing processor (CP), which is responsible for all the coordination and energy trading strategies, and the remaining remote radio heads (RRHs), that are in charge of all radio frequency operations. The data of information receiving terminals (ITs) is available at the CP and will be delivered to the multiple collaborative RRHs via high-capacity low-latency fronthaul links, e.g., optical fibre links. On the other hand, the ever-increasing energy cost has become a major OPEX as a result of striking rise of energy consumption induced by the ultra-dense RRHs deployment, which may result in a revenue threshold of the network operator. Consequently, equipping the RRHs with green energy technology that can harvest energy from environmental sources at a lower price for powering
next generation mobile communication networks, has become the potential solution. The local renewable energy generation in practice is, nevertheless, unequal since it highly depends on the efficiency of renewable energy harvesting devices and the location of installation sites. With the advanced smart grid technology, the implementation of two-way energy trading with the grid allows the RRHs to maintain their reliable operation in the case of insufficient local renewable energy via purchasing the inadequate amount of energy from the grid. Therefore, the network operator can maximally benefit from utilizing the local renewable energy and by selling the excessive energy back to the grid on an agreed price. Nevertheless, the aggregated power requirements by both receiving terminals may exceed the amount of power budget at the RRHs. Hence, the network operator has to purchase additional energy from the real-time market from the smart grid with a higher price, and may take a risk of losing the profit.

The introductory chapter consists of an outlined of the thesis statement that defines the open issues regarding interference and operational costs managements for next generation networks. Furthermore, the contributions of this thesis which are organized based on each subsequent chapters and a list of publications that are related to this thesis also have been highlighted.

Fundamental concepts of related topics were briefly reviewed in Chapter 2. A common class of optimal transmit downlink beamforming for multiple receiving terminals in a C-RAN powered by renewable energy technologies also has been provided in order to calculate the total transmit power with the given constraints. This non-convex optimization problem was transformed into a convex optimization form and the rank 1 constraint has been relaxed by using semidefinite programming (SDP) and semidefinite relaxation (SDR) approaches, respectively. Furthermore, a resource management and energy trading approach for energy cost saving in C-RAN powered by two-way energy cooperation between the smart grid and the renewable energy technologies has been introduced to adjust the non-uniform energy supplies and energy demands over the C-RAN. Related works comparable to the raised issues in the thesis are also discussed in this chapter.
Three different cooperative real-time energy trading strategies for downlink green C-RAN have been proposed in the first major contribution chapter, Chapter 3. The main objective was to jointly minimize the energy consumption and the real-time energy trading under the constraints of demand and supply power balancing at RRHs and QoS required by the information receiving terminals. For strategy 1, a sparse beamforming problem was formulated as an $\ell_0$-norm optimization problem and solve it using SDR and iterative reweighted $\ell_1$-norm approximation of $\ell_0$-norm. The strategies 2 and 3 were formulated as numerically tractable optimization problem and solved using the SDR approach. It has been proved that in terms of reducing total energy cost of the network operator, significant performance gain can be achieved by all the three proposed joint cooperative transmission and energy trading strategies, as compared to a baseline scheme that separately optimize the cooperative transmission and energy trading in a C-RAN scenario with realistic parameter settings.

A real-time energy trading strategy with simultaneous wireless information and power transfer (SWIPT) concept has been integrated in Chapter 4. Instead of designing the energy management for individual RRHs with a shortage of power as proposed in the previous chapter, the design strategies in Chapter 4 account for all RRHs with or without a shortage of power. The proposed strategies strike an optimum balance between the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, RRHs’ total transmit power and their maximum or total energy-purchase from the real-time market. Two strategies for optimizing the RRHs’ real-time energy trading with the smart grid have been presented. The first strategy was for minimizing the RRHs’ maximum real-time energy-purchase requests and the second strategy for minimizing the RRHs’ overall energy-purchase requests from the real-time market. Unlike Chapter 3 that take no consideration of realistic constraints on fronthaul capacity restrictions, this chapter was formulated with more realistic scenarios where RRHs was constrained with limited fronthaul capacities. An iterative energy receiving terminal (ET) authorization algorithm that allows only those ETs situated close enough to the RRHs to
receive wireless energy was introduced in order to maintain the efficiency of SWIPT technology. By employing the reweighted $\ell_1$-norm approximation for $\ell_0$-norm and SDR, the solution sparsity to the original non-convex optimization problems in (4.7) and (4.11) can be obtained. Simulation results confirmed that both of the proposed strategies outperform two other recently proposed schemes in terms of improving the energy efficiency and reducing total energy cost of the RRH in a realistic C-RAN scenario.

The works in previous chapters have been extended to a learning-based practical approach in Chapter 5. With various sizes of energy packages which were offered in the day-ahead market, the new responsibility of the CP is to determine the set of optimal sizes of the energy packages to be purchased for the RRHs on the basis of actual energy supply and demand, to further minimize the total energy cost of the network operator. Assuming that the RRHs have no initial knowledge of forthcoming energy consumption and renewable energy production in real-time energy trading, two combinatorial multi-armed bandit (CMAB) learning algorithms, namely, \textit{Forward CMAB (ForCMAB) Energy Trading} and \textit{Reverse CMAB (RevCMAB) Energy Trading}, have been proposed to observe the instantaneous energy demand and learn from the behaviour of cooperative energy trading in the green C-RAN with SWIPT. Simulation results confirmed that the two CMAB learning strategies outperform the strategies without learning approach, in terms of further reducing the total energy cost of the network operator.

A smart energy management strategy based on the CMAB approach for green C-RAN with SWIPT has been proposed in the last contribution chapter, Chapter 6. The combinatorial upper confidence bound (CUCB)-CMAB algorithms were introduced to adapt to the dynamic wireless channel conditions to further minimize the total energy cost of the network operator by maximizing the accumulated rewards obtained at each iteration. In contrast to the cooperative energy trading designs proposed in chapter 5, the CUCB-CMAB strategy will estimate the forthcoming energy demands and select an optimal set of energy packages to be purchased from the day-ahead market for the next time slot based on the observation of instanta-
neous energy demands at the current time slot and learning from the cooperative energy trading at previous time slots. Even though the regret of the CUCB-CMAB strategy is worst at the beginning of the learning process, the regrets start to drop at a great rate with the increasing number of time slots. It has been illustrated from the simulation results that the total energy cost can be saved up to 43 percent as compared to the baseline strategy and up to 11 percent as compared to the strategy without any learning-based approach.

7.2 Avenues of Future Research

Continuing from the aforementioned studies on energy and communication cooperation presented in this thesis, the current section suggests interesting directions for future research.

7.2.1 Self Energy Storage

In this thesis, no RRH in the green C-RAN is equipped with frequently rechargeable storage devices due to the cost consideration. However, in future, it is not impossible to install an energy storage at the master base station (MBS) in the C-RAN or can be employed at the RRHs with the advancement of battery technologies. The self energy storage management is expected to control unequal local renewable energy generation to match the energy request by receiving terminals that always change over time.

7.2.2 Neighbourhood Energy Sharing and Trading

Interestingly, self energy storages at the RRHs promote the neighbourhood energy sharing and cooperation in the C-RAN. Yet, how to enable energy sharing and cooperation between the RRHs requires communication compatibility and more coordination at the CP. Moreover, this collaboration can be expanded to the multiple self-interest systems that has been owned by different network operators. In this configuration, the CP at each C-RAN needs to establish a genuine joint energy and communication cooperation, since any present decisions made by the CPs would affect their total energy request to be served in the future. Presume in the energy sharing management, one selfish CP may request extra energy from the CP of the
other C-RAN and sell the energy to the grid to make a profit. Therefore, energy trading inter-system also need to be considered.

### 7.2.3 Game Theoretical Approach

To further motivate the potential RRHs with extra energy to assist in neighbourhood energy sharing and trading, practical energy and communications cooperation mechanisms need to be designed for RRHs by the game theoretical approach. For example, the RRHs could be selfish and prefer to store the harvested energy rather than to cooperate with the other RRHs. In this situation, that particular RRHs need to be offered some extra incentive to encourage them to be good players in a game. A good cooperation mechanism design is required to motivate all the players in a huge network cooperation to support the inter-system joint cooperation to a win-win situation for all systems involved.

### 7.2.4 Robust Sparse Beamforming

The sparse beamforming strategy used in this thesis works on the assumption that the cooperative transmitters have very accurate channel state information (CSI) about each others channel towards the receiver. In reality, however, the obtained CSI is not always accurate, e.g., due to location estimation errors. In such a case, sparse beamforming fails since the signals that arrive at the receiver are not synchronized or because the beamforming weights are not properly distributed among the cooperating nodes. Therefore, sparse beamforming should be made robust to such errors.

### 7.2.5 Multiple Input Multiple Output (MIMO)

In addition, both type of receiving terminals, i.e., ITs and ETs, and RRHs in C-RAN can be equipped with multiple antennas, i.e, multiple input multiple output (MIMO) configuration. With MIMO configuration, there will be more degree of freedom to effectively control interference. On the other hand, transmit and receive beamforming should be jointly designed. A question arising here is whether global optimality can be achieved by iteratively optimising transmit and receive beamforming. Complexity and signaling overhead are expected to significantly increase. Therefore,
practical solutions to the optimal beamforming and tradeoff between optimality and complexity are open problems for research.
Appendix A

Proof of Lemma 1

This section provides a proof for lemma 1 in the context of optimization problem in (4.10), which can be similarly extended to the context of the optimization problem in (4.12). Since the optimization problem in (4.10) is convex and satisfies the Slater’s condition, strong duality holds [68] and its Lagrangian is

\[
\mathcal{L}(W_i, V_e, Y_i, Z_e, V_i, \rho_e, \pi_e, \varphi_i, \phi_i, \tau_i, \psi, \epsilon_i, \rho_i, \zeta_i) = \sum_{i \in L_i} \text{tr}(Q_i W_i) - \sum_{i \in L_i} \text{tr}(W_i (Y_i + \frac{v_i H_i}{\gamma_i})) \\
+ \sum_{e \in L_e} \text{tr}(Q_e V_e) - \sum_{e \in L_e} \text{tr}(V_e (Z_e + \frac{\rho_e G_e}{P_e^{[\text{min}]}}) + \Xi, \quad (A.1)
\]

where

\[
Q_i = \alpha \sum_{n \in L_b} \xi_{ni} D_n + \beta I + \sum_{i \in L_i, j \neq i} v_j H_j - \sum_{e \in L_e} \frac{\rho_e G_e}{P_e^{[\text{min}]}} \\
- \sum_{z \in L_e^{[\text{idle}]}} F_z \pi_z + \sum_{n \in L_b} (\varphi_i + \phi_i + \tau_i \xi_{ni} \hat{R}_i) D_n, \quad (A.2)
\]

\[
Q_e = \alpha \sum_{n \in L_b} \kappa_{ne} D_n + \beta I + \sum_{i \in L_i} v_i H_i - \sum_{e \in L_e, j \neq e} \frac{\rho_e G_j}{P_e^{[\text{min}]}} \\
- \sum_{z \in L_e^{[\text{idle}]}} F_z \pi_z + \sum_{n \in L_b} (\varphi_i + \phi_i) D_n, \quad (A.3)
\]
\[ \Xi = \sum_{n \in L_b} (\psi - \varphi_n)B_n^{[\text{ahead}]} + \sum_{n \in L_b} (\psi - \varphi_n - \varepsilon_n)B_n^{[\text{real}]} + \sum_{i \in L_i} \nu_i \sigma_i^2 + \sum_{e \in L_e} \rho_e \eta_e^{-1} + \sum_{z \in L_z^{[\text{idle}]} \eta_z^{-1} - \psi P_{CP}^{[\text{max}]} - \sum_{n \in L_b} (\psi - \varphi_n - \varepsilon_n)B_n^{[\text{real}]} + \sum_{i \in L_i} \nu_i \sigma_i^2 + \sum_{e \in L_e} \rho_e \eta_e^{-1} - \sum_{n \in L_b} (\tau_n C_n^{[\text{b-limit}]} + \rho_n S_n - \varsigma_n \chi - \varsigma_n \zeta B_n^{[\text{real}]}\right) + \chi. \] (A.4)

\( \Xi \) is the summation of the terms that does not involve any \( W_i \) and \( V_e \). The matrices \( Y_i \) and \( Z_e \) as well as the set \( \Theta = \{v_i, \rho_e, \pi_z, \varphi_n, \tau_n, \psi, \varepsilon_n, \rho_n, \varsigma_n\} \) denote, respectively, the matrix dual variable of \( C_1 \) and \( C_12 \) as well as the set of scalar Lagrange multipliers of the primal constraints \( C1-C10 \). Then, the dual problem can be written as

\[ \max_{\Theta \geq 0, Y_i, Z_e \geq 0} \min_{W_i, V_e, \chi} \mathcal{L}(W_i, V_e, \chi, Y_i, Z_e, \Theta), \] (A.5)

where \( \Theta \geq 0 \) implies that all of the scalar dual variables within the set \( \Theta \) are non-negative, for the sake of notational simplicity. Let \( \{W_i^*, V_e^*, \chi^*\} \) and \( \{Y_i^*, Z_e^*, \Theta^*\} \) be defined as the set of optimal primal and dual variables of (4.10), respectively. The dual problem in (A.5) can be expressed as

\[ \min_{W_i} \mathcal{L}(W_i, V_e^*, \chi^*, Y_i^*, Z_e^*, \Theta^*), \] (A.6)

\[ \min_{V_e} \mathcal{L}(V_e, W_i^*, \chi^*, Y_i^*, Z_e^*, \Theta^*), \] (A.7)

and the Karush-Kuhn-Tucker (KKT) conditions are given by

\[ \Theta^* \geq 0, Y_i^* \geq 0, Y_i^* W_i^* = 0, \forall i \in L_i, \] (A.8)

\[ Z_e^* \geq 0, Z_e^* V_e^* = 0, \forall e \in L_e, \] (A.9)

\[ Q_i^* - (Y_i^* + \frac{V_i^T H_i}{\gamma_i}) = 0, \forall i \in L_i, \] (A.10)

\[ Q_e^* - (Z_e^* + \frac{G_e}{\rho_e^{[\min]}}) = 0, \forall e \in L_e, \] (A.11)
where \( Q_i^* \) and \( Q_e^* \) are obtained by substituting the optimal dual variables into the expressions in (A.2) and (A.3), respectively. In the sequel, it is shown by contradiction that \( \text{rank}(V_e^*) \leq 1 \) holds with probability one. It is first proved by contradiction that \( Q_e^* \) is a positive definite matrix with probability one. Assuming \( Q_e^* \) is a non-positive definite matrix, one of the optimal solutions of (A.7) can be chosen as \( V_e = h v_e v_e^H \), where \( h > 0 \) is a scaling factor and \( v_e \) is the eigenvector corresponding to one of the non-positive eigenvalues of \( Q_e^* \). Substituting \( V_e = h v_e v_e^H \) into (A.7) gives

\[
\min_{V_e} \mathcal{L}(V_e, W_i^*, r_i^*, Y_i^*, Z_e^*, \Theta^*)
\]

\[
= \sum_{e \in \mathcal{L}_e} \text{tr}(h Q_e^* v_e v_e^H) - h \sum_{e \in \mathcal{L}_e} \text{tr}(v_e^H (Z_e^* + \frac{\rho_e G_e}{P_e^{[\text{min}]}}) v_e)
\]

\[
+ \left( \sum_{i \in \mathcal{L}_i} \text{tr}(Q_i^* W_i^*) - \sum_{i \in \mathcal{L}_i} \text{tr}(W_i^* (Y_i^* + \frac{v_i^H H_i}{\gamma_i})) + \Theta^* \right),
\]

where \( \sum_{e \in \mathcal{L}_e} \text{tr}(h Q_e^* v_e v_e^H) \) is non-positive and as \( h \to \infty \), \( -h \sum_{e \in \mathcal{L}_e} \text{tr}(v_e^H (Z_e^* + \frac{\rho_e G_e}{P_e^{[\text{min}]}}) v_e) \) may go to negative infinity, which results in an unbounded dual optimal value. However, the optimal value of the primal problem is non-negative, thus strong duality does not hold which induces a contradiction. Therefore, \( Q_e^* \) is a positive definite matrix with probability one and \( \text{rank}(Q_e^*) = MN \), provided that channel vectors \( h_i \), \( g_e \) and \( f_z \) are independently distributed. Then the following inequality holds as per (A.11) and properties of rank of matrix:

\[
\text{rank}(Q_e^*) = MN = \text{rank}(Z_e^* + \frac{\rho_e G_e}{P_e^{[\text{min}]}})
\]

\[
\leq \text{rank}(Z_e^*) + \text{rank}(\frac{\rho_e G_e}{P_e^{[\text{min}]}})
\]

\[
\Rightarrow \text{rank}(Z_e^*) \geq MN - 1. \tag{A.13}
\]

Furthermore, the KKT condition in (A.9), i.e., \( Z_e^* V_e^* = 0 \), implies

\[
\text{rank}(Z_e^*) \leq MN - \text{rank}(V_e^*). \tag{A.14}
\]
If the desired $P_e^{[\min]}$ is larger than the power that can be transferred to the ET by the ambient interference, then $V^*_e \neq 0$, otherwise $V^*_e = 0$. On the other hand, an inspection of the results in (A.13) and (A.14) implies that for $V^*_e \neq 0$, $\text{rank}(Z^*_e) = MN - 1$ must hold. Note also that according to the KKT condition in (A.9), the columns of $V^*_e$ are in the null space of $Z^*_e$. Therefore, when $V_e \neq 0$, $\text{rank}(V^*_e) = 1$ holds with probability one, whereas $V^*_e = 0$ implies $\text{rank}(V^*_e) = 0$. Hence, $\text{rank}(V^*_e) \leq 1$ holds with probability one.

By following the similar steps, it can be easily shown that in order to satisfy the minimum SINR requirements in the constraint C1 of (4.12), $\text{rank}(W^*_i) = 1$ must hold with probability one. This thus completes the proof of Lemma 1 for problem (4.10). Furthermore, Lemma 1 also holds for the optimization problem in (4.12) and can be proven straightforwardly by following the similar steps as stated for the optimization problem in (4.10).
Bibliography


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