



Addis Ababa University

IT Doctoral Program

**An Evolutionary Cluster-Game Approach for WSNs
in Non-Collaborative Settings**

By

Ketema Adere Gemed

December 2018

Addis Ababa University

IT Doctoral Program

**An Evolutionary Cluster-Game Approach for WSNs in
Non-Collaborative Settings**

**A Dissertation submitted in partial fulfillment of the requirement
for the Degree of Doctor of Philosophy in IP Networking and
Wireless Mobile Internet**

By

Ketema Adere Gemedu

Supervisors:

Gabriele Gianini (PhD), University of Milan, Italy

Mulugeta Libsie (PhD), Addis Ababa University, Ethiopia

Addis Ababa University

IT Doctoral Program

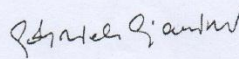
An Evolutionary Cluster-Game Approach for WSNs in Non-Collaborative Settings

By

Ketema Adere Gemedu

Approval of Board of PhD Dissertation Committees

Gabriele Gianini (PhD)
Advisor

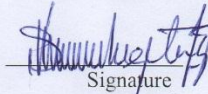


January 17, 2019

Signature

Date

Mulugeta Libsie (PhD)
Co-advisor

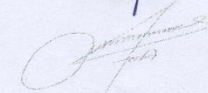


17/01/2019

Signature

Date

Towfik Jemal (PhD., Dr.-Ing.)
External Examiner

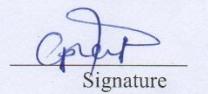


14/01/2019

Signature

Date

Ephrem Teshale (PhD)
Internal Examiner



16/01/2019

Signature

Date

Yihenew Wondie (Dr. Eng.)
IPNWMI Track Coordinator



17/01/2019

Signature

Date

DEDICATION

I would like to dedicate this dissertation to the memory of my late Father (1934 - 2012), Obbo Adere Gameda who nurtured me with the will to take my study to the highest level. Although I was shocked to have lost you during the early days of my PhD study, I have eventually made it thanks to the wisdom you instilled in me as a child. Let Your Soul Rest in Peace!

ACKNOWLEDGEMENT

First and foremost, I would like to extend my heartfelt thanks and gratitude to my advisor Prof. Gabriele Gianini for his insightful advice and guidance that capacitated me to manage the challenges in the course of the study. I am also indebted to him for his warm discussions on the notion of evolutionary game theory from which the research method used in this dissertation have been derived and designed. I am forever grateful to him for being a wonderful mentor in encouraging and supporting me to grow as an academic researcher.

My heartfelt gratitude and sincere appreciation also go to my co-advisor Dr. Mulugeta Libsie for his continuous guidance and endless support technically and professionally in the course of doing this PhD research. I warmly thank him for his invaluable discussions, informative and educative comments and feedbacks which I have enjoyed. His insights and words of encouragement have often inspired me and renewed my hopes that enabled me to complete my dissertation.

I am deeply indebted to Dr. Eng. Yihenew Wondie for being a member of my PhD examination committee. His kindly treatment and unreserved help as an IPNWMI track coordinator is indeed incredible. I would also like to extend my thanks to the other members of the examination committee Dr. Ing. Towfic Jemal and Dr. Ephrem Teshale for their useful comments.

I also want to extend my thanks to IT Doctoral Program of Addis Ababa University for offering me the chance to be enrolled in this study as well as for availing the necessary educational facilities, arranging international research trainings and research experiences. CITRI research members Dr. Salehu Anteneh, Dr. Dejene Ejigu, Dr. Solomon Atnafu, and Dr. Fekade Getahun deserve special acknowledgement for rendering me the support and guidance I demanded. Their tremendous and thoughtful discussions have greatly contributed to the success of my study. I also wish to thank my fellow research colleagues Dr. Dawit Kifle, Fiseha Bayu, Dr. Meshesha Legesse, Dr. Melkamu Beyene, Dr. Samuel Asferaw, and Dr. Esubalew Yitayal for the valuable discussions and suggestions which eventually made this work possible.

My thank also goes to ASTU for granting me study leave with the necessary benefits, without which I could not have been able to join my PhD study. To all of my friends and colleagues at ASTU, I say, you deserve my eternal gratitude for the discussions we had on various issues of

interest. I would like to express my greatest appreciation to the various people who have shared their opinions and experiences from which I received crucial information during my study. Especially, I have to thank Dr. Kassaye Gutama, Dr. Jira Mekonnen, Dr. Ejera Batu, Dr. Alemu Disessa, Adugna Abdisa, Tsigu Birehanu, Tadesse Joriye, and Dr. Kanani Alemu for making my life much easier in dealing with this work.

I feel very much honored to thank INSA de Lyon University, France, and Milan University, Italy, who allowed me to work in their research laboratories without restrictions. In these laboratories, I had the chance to learn from the rich experiences of the various academicians, researchers, and experts. Particularly, my special thanks go to Prof. Lionel Brunie, Prof. Jean-Marc Pierson, Dr. Pierre-Edouard Portier, Dr. Nadia Bennani, Mrs. Valerie Lebey, and Mrs. Dominique Barriere for their invaluable feedbacks and other facilitations that they rendered me. I am deeply grateful to French Ministry of Research, the COOPERA program for providing me the financial support without which the realization of this work could not have been possible. Thank you so much for all the kindness.

I am also very much grateful to my family members for their sacrifice and patience throughout the whole journey of my doctoral study. Without their unconditional and unwavering love and support, I would not have reached this far.

Last but not least, I thank God for His generosity and help throughout my life.

Ketema Adere Gemedo,

December 18, 2018

ABSTRACT

In the designing of Wireless Sensor Networks (WSNs), it is often assumed that each sensor node faithfully follows the prescribed conventional standards without any deviation. Nevertheless, when WSNs that are located in the same vicinity are owned and managed by different network authorities, individual nodes will likely do what is most beneficial to its governing authority. As such a node may be reluctant to forward the packets of other authority's nodes, so as to preserve its resources (for instance, energy and CPU time).

Sensor nodes are small in size and have a very limited amount of energy which considerably limits the lifetime of WSNs if their resources could not be properly utilized. Cluster-based routing algorithms preserve energy by grouping nodes into multiple clusters. Moreover, it selects a single node in each cluster as the Cluster Head (CH) to communicate with a Base Station (BS) on behalf of other nodes. In an ideal collaborative setting, nodes should alternate the role of CH according to some fairness rule. However, in reality, a selfish (non-cooperative) node might refuse to volunteer: cooperation is not guaranteed in Multi-class WSNs (MWSNs). The degree of compliance of nodes to this fairness rule can greatly influence the Quality of Service (QoS) provided by the network. Consequently, the first and foremost step to address such a problem consists of building a model that captures and mitigates the essential aspects of an existing physical phenomenon, and then, designing an energy-efficient routing algorithm.

In this dissertation, we developed a model of an Evolutionary Collaborative Game (ECG): an evolutionary dynamics whereby players (i.e., sensor nodes) interact by adopting either cooperative or non-cooperative strategy and, then, evaluating their packet forwarding benefits. An analytic model of nodes' population evolution, called *replicator dynamics* is also systematically derived as a guide in the choice of the mechanisms. Nodes adapt their strategies on the basis of the outcomes of the interactions with other nodes and converge to an ESS. This corresponds to the anticipated behavioral outcomes in the dynamics whereby the population of nodes reaches a stable equilibrium.

Considering the ESS outcome that has been a desirable state of the system, we propose two algorithms for WSNs in non-collaborative settings. The first algorithm consists of cluster-based Collaborative Packets Forwarding (CPF), where nodes in the population game interact (i.e., each node interacts to any others) with the same probability. By introducing a rewarding

mechanism (also known as an incentive), it has been observed that nodes evolve and reach a collaborative stable equilibrium as per our conducted analysis that has been shown both analytically - in a stylized scenario, and numerically - by using simulations, (assuming the relations between payoff parameters (cost-to-benefit ratio (w) and reward-to-benefit ratio (d)) and the number of nodes (N)). Given the value of d is constant, it is observed that the quantified equilibrium decreases when the values of w and N increase, but when the value of d decreases the equilibrium drops more rapidly as a large number of nodes switch into non-collaborative behavior in order to conserve their resources.

Then, the achievements of collaborative equilibrium and cooperative-rate have been evaluated in the development of CH-determination of CPF algorithm. As such, CH role is determined and rotated based on the potential collaborations that the individual nodes made. The studied simulation results have revealed that CPF will be able to conserve the remaining energy of networks when comparing it with default case (i.e., Non-collaborative Packets Forwarding (NcPF) algorithm).

An algorithm called GREET (evolutionary Game theory based Energy Efficient cluster-head determination algorithm) has also been proposed by assuming that nodes only interact with their neighboring nodes. In the evolutionary cluster-game, it is observed that the stable equilibrium has been reached without the requirement of any external enforcement mechanism. The probability of volunteering as CH candidate decreases with the growth of w and M (number of nodes in the given cluster). In the achievement of equilibrium probability, CH-enabled nodes start to decide whether to be a candidate CH or not in the current round. Then, considering the energy level of currently contested candidates (in case they are more than two), appointed-CH would be determined to represent its members in transmitting packets. Moreover, nodes with minimum residual energy will stay in CH-disallowed state until their energy level is on equal footing with others. This process, in turn, helps the algorithm to balance the energy consumption of nodes.

Subsequently, simulation results for both CPF and GREET were analyzed and compared with respect to other standard WSN algorithms such as LEACH and CROSS. It is found that GREET outperforms all of them in terms of network lifetimes and packet throughputs. The reason is that the achievement of nodes' collaborative equilibriums is balanced as well as the

role of CH is uniformly distributed and fairly rotated in extending energy utilizations. Although global information is required both in CPF and CROSS, CPF performs better than CROSS for certain payoff functions.

Keywords: Cluster-based CPF Algorithm, Energy Efficient Algorithm, Evolutionary Cluster-Game, Evolutionary Collaborative-Game, GREET, MWSNs, Network Lifetime, Non-collaborative Nodes.

TABLE OF CONTENTS	PAGE
ACKNOWLEDGEMENT	i
ABSTRACT	iii
LIST OF FIGURES	iv
LIST OF TABLES	vi
LIST OF ACRONYMS	vii
CHAPTER ONE: INTRODUCTION.....	1
1.1 Background.....	1
1.2 Terminologies.....	5
1.3 Motivations of this Dissertation	7
1.4 Statement of the Problem	9
1.5 Research Objective.....	11
1.6 Research Methodology.....	11
1.7 Organization of the Dissertation.....	13
CHAPTER TWO: LITERATURE REVIEW	15
2.1 Overview of WSNs.....	15
2.1.1 Characteristics of WSNs.....	16
2.1.2 Applications of WSNs	18
2.1.3 Topology of WSNs.....	18
2.1.4 Routing Algorithms.....	19
2.2 Communication Energy Preservation	24
2.2.1 Cluster-Based Routing Algorithm	24
2.2.2 Radio Energy Model	32
2.2.3 Network Lifetime.....	34
2.3 Overview of GT Approaches	36
2.4 Evolutionary Population Games	40
2.4.1 Social Dilemma Games	41
2.4.2 Dynamic Equilibrium Behaviors.....	46
2.5 The Role of GTs in Designing WSNs	48
2.5.1 GTs for Routing Algorithm	49
2.5.2 GTs for Power Management	51

TABLE OF CONTENTS

2.5.3	GTs for Topology Control	52
2.5.4	GTs for WSN Security	53
2.6	Summary	54
CHAPTER THREE: RELATED WORK.....		56
3.1	Methods to Mitigate the Selfish Nodes	56
3.2	Multi-class Sensor Networks	63
3.3	GT for Mitigating Selfishness in the Cluster-Based Algorithms.....	66
3.4	Summary	76
CHAPTER FOUR: NODES COLLABORATION WITH EVOLUTIONARY DYNAMICS		79
4.1	An Overview of Nodes Collaborative Designing.....	79
4.2	A Mechanism of Mutual Collaboration.....	81
4.2.1	Representation of an Evolutionary Approach	81
4.2.2	ECG Model	82
4.3	An Evolutionary Dynamic Model	83
4.3.1	Dynamic Equation.....	84
4.3.2	Pair-wise Contest Game.....	87
4.3.3	Multi-players Contest Game	89
4.4	The Analytic Model of Dynamic System	90
4.5	Cluster-Based CPF Algorithm	100
4.5.1	State of FH-Determinations.....	100
4.5.2	The Default NcPF Algorithm	104
4.6	Summary	107
CHAPTER FIVE: GREET ALGORITHM.....		109
5.1	An Overview	109
5.2	Analytic Model of Dynamic System: M-node Game	110
5.2.1	An Evolutionary Cluster-Game	110
5.2.2	Analytic Equilibrium Dynamics.....	111
5.3	The Detailed Description of GREET Algorithm	116
5.3.1	Initiation Phase.....	117
5.3.1	Set-up Phase.....	118
5.3.2	Data Transmission Phase.....	124

TABLE OF CONTENTS

5.3.3	Synchronization and Scheduling.....	124
5.4	GREET: Performance Assessment.....	125
5.4.1	Energy Cost at Equilibrium Evolution.....	129
5.4.2	Players Grouping in Agencies	133
5.5	Summary	134
CHAPTER SIX: PERFORMANCE EVALUATIONS.....		137
6.1	An Overview of Simulation Systems.....	137
6.2	Basic Scenario-Specific Assumptions and Estimations.....	138
6.3	Simulation Results and Discussions	143
6.4	Summary	153
CHAPTER SEVEN: CONCLUSION AND FUTURE WORKS		155
7.1	Conclusion.....	155
7.2	Summary of Our Contributions.....	157
7.3	Future Works.....	160
BIBLIOGRAPHY		163
APPENDIXES		181
A.	The Effect of Selfish Nodes on the Network Performances.....	181
B.	List of Publications.....	183

LIST OF FIGURES

<i>Figure 2.1: The General Topological Representations of WSNs: (a) Single-hop Flat Model; (b) Multi-hop Flat Model; (c) Single-hop Clustering Model; and (d) Multi-hop Clustering Model</i>	<i>20</i>
<i>Figure 2.2: Taxonomy of Routing Algorithms in WSNs</i>	<i>22</i>
<i>Figure 2.3: Sensor Node's Radio Energy Dissipation Model</i>	<i>33</i>
<i>Figure 2.4: Overview of the Possible Dynamic Equilibriums: (a) and (b) Represent Dominance Situations, either by D's or C's respectively; (c) and (d) Specify the Two Types of Internal Equilibrium Points, Coexistence and Coordination respectively</i>	<i>47</i>
<i>Figure 2.5: The Relationship between WSNs and GTs</i>	<i>49</i>
<i>Figure 4.1: The Equilibrium Probability of Collaborative Nodes ($N = 6$) versus w; when the Value of d varies</i>	<i>97</i>
<i>Figure 4.2: The Equilibrium Probability of Collaborative Nodes ($N = 4, N = 10, N = 20, N = 30$) versus w; when $d = 0.6$</i>	<i>98</i>
<i>Figure 4.3: The Effect of Number of Sensor Nodes ($N = 50$) on Collaborative Equilibrium, for the Parameter $d = 0.8$ and $w = 0.1$</i>	<i>99</i>
<i>Figure 4.4: FH-Determination State Diagram for Cluster-based CPF Algorithm</i>	<i>103</i>
<i>Figure 4.5: The Number of Sensor Nodes with Positive Residual Energy for CPF and NcPF Algorithms with Respect to Different Payoff Functions: a) Payoff Parameters, $d = 0.5$ and w (0.8, 0.5, 0.1); b) Payoff Parameters, $d = 0.7$ and w (0.8, 0.5, 0.1); c) Payoff Parameters, $d = 0.9$ and w (0.8, 0.5, 0.1)</i>	<i>106</i>
<i>Figure 5.1: Equilibrium Probability (Probability of Volunteering as Candidate CH) as a Function of the Cost-to-benefit ratio w</i>	<i>115</i>
<i>Figure 5.2: Equilibrium Probability (Probability of Volunteering as Candidate Cluster Head) as a Function of the Number of Nodes M</i>	<i>116</i>
<i>Figure 5.3: Phases of GREET Cluster Routing Algorithm</i>	<i>117</i>

TABLE OF CONTENTS

Figure 5.4: A Simple GREETING_MSG Message Format	118
Figure 5.5: Representation of Radio Transmission Range ($R_{contest}$) for Nodes N1, N2 and N3	119
Figure 5.6: State Diagram for the Sensor Node	122
Figure 6.1: The First Node Dead for Different Values of w	144
Figure 6.2: The Last Node Dead for Different Values of w	145
Figure 6.3: The Number of Sensor Nodes with Positive Residual Energy in LEACH, CROSS and CPF Algorithm with Respect to Different Values of Payoff Functions: a) Payoff Parameters, $d = 0.5$ and $w(0.1, 0.5, 0.9)$; b) Payoff Parameters, $d = 0.7$ and $w(0.1, 0.5, 0.9)$; c) Payoff Parameters, $d = 0.9$ and $w(0.1, 0.5, 0.9)$	147
Figure 6.4: The First Node Dead for Different Values of w	149
Figure 6.5: The Last Node Dead for Different Values of w	150
Figure 6.6: The Number of Nodes with Positive Residual Power	151
Figure 6.7: Average data sent to the BS (number of packets)	152
Figure A.1: Network Lifetime as the First and Last Nodes Die	181
Figure A.2: Packet Throughput and Packet Retransmission Attempts	182

LIST OF TABLES

<i>Table 2.1: Typical Operations and Values of Radio Energy Expenditure Parameters</i>	<i>34</i>
<i>Table 2.2: The Possible Payoff Notation of Symmetric Game</i>	<i>41</i>
<i>Table 2.3: A Partitioning of the S-T Plane which Displays the 2x2 Games of Symmetric.....</i>	<i>43</i>
<i>Table 6.1: Network Simulating Setup Parameters</i>	<i>139</i>

LIST OF ACRONYMS

ACHGT	Adaptive Clustering Hierarchy based on Game-theoretic Technique
AODV	Ad hoc On-Demand Distance Vector
BCDCP	Base-station Controlled Dynamic Clustering Protocol
BCSP	Base-station Centralized Simple Protocol
BS	Base Station
CH	Cluster Head
CGT	Classical Game Theory
CORE	COst- and REward-based clustering
CPF	Collaborative Packets Forwarding
CPU	Central Processing Unit
CROSS	Clustered Routing for Selfish Sensors
CSMA/CA	Media Access Control/Collusion Avoidance
DEEH	Dynamic Energy-Efficient Hierarchical clustering algorithm
DEER	Distributed Energy-Economical Routing
DEGRA	Density-based Energy-efficient Game-theoretic Routing Algorithm
DR-OSTC	Distributed Randomized – Orthogonal Space-Time Coding
DSR	Dynamic Source Routing
ECG	Evolutionary Collaborative Game
EECS	Energy Efficient Clustering Scheme
EGT	Evolutionary Game Theory
ERA	Energy Residue Aware cluster-based algorithm
ESS	Evolutionary Stable State or Strategy
FDMA	Frequency Division Multiple Access
FND	First Node Dead
FH	Forwarder-Head
GPS	Global Positioning System

LIST OF ACRONYMS

GREET	evolutionary Game theory based Energy Efficient cluster-head determination algorithm
GT	Game Theory
GTRF	Game Theory based Real time Fault tolerant routing protocol
HBDR	Heterogeneous Balanced Data Routing algorithm
HEED	Hybrid Energy-Efficient Distributed clustering
IEEE	Institute of Electrical and Electronics Engineers
IN	Inspector Node
LEACH	Low Energy Adaptive Clustering Hierarchy
LEACH-C	LEACH-Centralized
LGCA	Localized Game-theoretical Clustering Algorithm
LND	Last Node Dead
MAC	Medium Access Control
MANET	Mobile Ad hoc Network
MCG	Multi-players Contest Game
MN	Member Node
MWSN	Multi-class Wireless Sensor Network
NcPF	Non-collaborative Packets Forwarding
NE	Nash Equilibrium
PEGASIS	Power Efficient Gathering in Sensor Information System
QoS	Quality of Service
RRCH	Round-Robin Cluster Header
TEER	Trustworthy Energy Efficient Routing algorithm
TDMA	Time Division Multiple Access
WCA	Weighted Clustering Algorithm
WSN	Wireless Sensor Network

CHAPTER ONE: INTRODUCTION

This chapter presents a brief background of the research problems that have been investigated, motivation of the research and objectives of this research. In addition, methodology that has applied to achieve the dissertation objectives has been described. Finally, the organization of chapters of this dissertation is outlined.

1.1 Background

WSNs consist of hundreds and/or thousands of sensor nodes that distributed over a geographical area using wireless links [1], [2], [3], [4]. These nodes are helpful for observing physical phenomena and making observation-based choices in processing the data [2], [4]. Tiny nodes collect and route data, possibly through multiple intermediate nodes, to a central node called the BS for further processing and decision making. The BS operates as a data sink and as gateways to other interconnected networks such as the Internet. In addition, it has a reliable power supply and a higher processing capability with respect to other nodes.

Nodes in WSNs are constrained in resources: they have limited memory storage, limited energy supply, and limited computing capability. Thus, the designing of algorithms or protocols should take into account such constraints. An effective approach that is able to preserve communication resources so as to extend the lifetime of sensor networks is the cluster-based routing algorithm, which is based on the neighborhoods grouping [5], [6], [7], [8]. In this algorithm, nodes are arranged into clusters, and, in each cluster, the task of communicating packets is delegated to a single node (i.e., CH). The CH receives data from its members, aggregates and forwards to the BS. In this system, nodes are also expected to contribute their resources locally, by forwarding the packets to one another. In recent years, a large number of algorithms have been proposed and some of these include LEACH [5], LEACH-C [6], PEGASIS [9], BCDCP [10], BCSP [11], WCA [12], and HEED [13].

In the course of designing these algorithms, the philosophy of the cooperation between neighboring nodes' has fundamentally been considered. In this setting, resource-constrained nodes commonly received enormous advantages: optimized communication energy and bandwidth, extended network service availability (eg., network lifetime), enhanced robustness

and scalability of network. Nevertheless, the research has witnessed that individual authority who own these nodes generally behave in a non-cooperative manner that may greatly reduce the expected performances [14], [15], [16]. In such perspective, self-optimizing intermediate nodes do not want to consume their limited resources for routing the packets of other nodes. In these types of networks, the network would solely run by the operation of the end users rather than relying on any priorly established infrastructure or centralized administration [17], [18], [19], [20], [21], [22].

The previously conducted studies claimed that the performance of networks has extremely been degraded by the presence of misbehaving nodes, as it is shown in [23], [24], [25], [26]. The result of a study in [24] shows that the QoS is vastly reduced as the concentration level increased: the probability of packets reachability (throughput) comes down to nearly 50% whereas the average of hop count reaches to a maximum of 2.5 times, and the percentage of dropped packet goes up to nearly 60%. The performance of an ordinary cluster-based routing is investigated in [25]: packet throughputs are reduced. Moreover, in [26], the shortest path routing algorithm is studied: packets reachability decreases as the number of selfish users increase. Thus, in the presence of such nodes, the functionality of the networks is massively affected. When their concentration levels are large, they might cause a passive denial of service which might even lead to the malfunctioning of the whole network communication.

Such behaviors are performed by individual participants that intend to benefit from the whole network without contributing their fair share to it. One of the reasons why this happens in the distributed and collocated network is because thousands of nodes are left unattended after deployment. The tendency of a node to conserve its resources by requesting the others to forward its packets dubs it selfishly: its primary goal is to maximize the benefits to its agency, even at the expenses of other nodes. Thus, developing a model that fosters this selfishness towards achieving effective resource utilization is a point of interest in this study. In such case, collaboratively operated networks must be ensured and standardized. Generally, adhering to such policies can put this network performance at a better level of enactment. In fact, this is a big challenge in the modern multi-authority and multi-domain also commonly referred to as Multi-class Wireless Sensor Networks (MWSNs) design [17], [18], [19], [20], [21], [22], [27].

Until few years ago, the typical operation of a distributed WSNs architecture could be modeled as the enactment of a collaborative protocol by networked nodes or agents, faithfully executing, to the best of their capabilities, the programmed behavior, assigned to them by the system designer. Within such blind compliance, the networked nodes could be aware of the degree of consumption of their own resources, needed for performing the specific tasks, but would not be allowed to adopt any selfish behavior implying a deviation from the protocol. In that frame, the protocol designer's choices would typically represent a tradeoff between the degree of attainment of the network's goals (e.g., in terms of communication latency and efficiency, reliability or performance) and the level of resource consumption of the network as a whole (e.g., in terms of computational and communication resources).

In today networks – often resulting from the free aggregation of nodes or agents operated by selfish parties, whose goals and interests are typically not aligned – such a frame turns out not to be adequate. In order to better capture all the aspects and forces acting in and over the system, the designed model must take into account the agents' individual preferences, as well as the fact that each agent could be aware of the other agents' preferences and selfishness, and perform strategic choices consequently. The natural frame for modeling such interdependent and possibly interactive decision landscape is Game Theory (GT).

GT has the capabilities of tackling the issues of selfish agents that are capable of strategic reasoning [28], [29], [30]. It can be used to predict the outcome which will be the rational agents' behavior resulting from a specific system setup in terms of joint strategies of all the rational agents. This solution is called Nash Equilibrium (NE), it consists of a strategy profile (a collection of strategies, one for each player in the game) from which no individual has the interest to deviate unilaterally. The intuition behind NE is that it represents a possible stable state to play. A game designer-changing the incentives of a game for each combination of contingencies - can nudge the game's equilibrium; for instance, transform an equilibrium based on non-collaborative strategies into a collaborative-based one. The area of GT which models fully rational players adopting strategic reasoning is commonly called Classical GT as opposed to other areas where the player is endowed with lesser forms of rationality [31], [32], [33], [34].

A model of GT approaches extensively applied in WSNs design to mitigate the behaviors of individual nodes [14], [15], [16], [17], [35], [36], [37]. The game analyzes the strategies of non-

alien nodes' interaction in the algorithms. Considering the existing algorithms, their contributions and limitations are analyzed in Sections 3.2, 3.3 and 3.4. In addition to GT approaches, several methods or techniques are available in the ongoing research trends. Some of them are grouped as: identification and isolation [38], [39], [40], [41], [42], trust and reputation-based [43], [44], [45], and credit-payment [46], [47], [48], [49]; in the former two methods once selfish nodes are identified, they are punished or isolated - denied from utilizing the network resources while in the latter method, the cooperative nodes are incentivized. Because of these reasons, both the communication channels and the behavior of nodes are continuously monitored in these techniques. Most of the available works with respect to the development of WSNs are described in detail in Section 3.1, whereas their level of vulnerability in delivering reliable communications will be investigated in Section 3.4.

In this dissertation, a special area of GT, assuming limited rationality, is also called EGT has been adopted into the ECG model in order to regulate the behaviors of self-interested nodes. Thus, by modeling a system of nodes, first through replicator dynamics, then by a more realistic WSN simulation, we have proposed cluster-based routing algorithms, viz. CPF and GREET. In these modeling contexts, each node player is assumed not to use strategic reasoning, but just to learn from recent experience and adapt its strategy consequently, pursuing a short-term selfish goal. In a WSN setting, EGT requires the individual node to simply observe the behavior of its neighboring nodes and to change its own strategies based on the observation [29], [31]. As a result, sub-populations of interacting nodes evolve their behaviors: the percentage of nodes adopting any specific strategy evolves with time (also represented as a round). In some cases, the percentages of the different strategies in a population can become stable, as such; this situation is referred to as an evolutionary equilibrium, i.e., simply ESS profile.

A common tool assumed in EGT for analytically modeling the evolutionary population is the so-called replicator dynamics [50], [51]. This model of the dynamics posits that – from a round of interactions to the next – the proportion of sensor nodes using a definite strategy increases proportionally to the relative advantage provided by the strategy with respect to the average payoff of the population. Replicator dynamics is one of the stylized models that use the population approximation. This approximation assumes that the ensemble of individuals participating in the process is so well-mixed, that any individual node has the same probability

of meeting any other individuals. The population approximation does not take into account the fact that individuals are bound by physical constraints to specific regions of space and interact only with neighbors; however, it can provide a “first-order” analytic model of the phenomena, especially good if the individuals are characterized by a high mobility. The addition of physical space to the picture is most of the time achieved by giving up the analytic tractability and passing to simulative models.

In developing this model, first we have analyzed a two-node contest game to gain some insight, and then extended the observation into a multi-node contest game. Using both theoretical and simulation analyses, we have enumerated an achievement of ESS where nodes reached collaborative equilibrium. Then, we have developed detailed algorithms for CH determination and studied their effectiveness by simulation in a structured population setting: we have checked that the system converges to equilibrium. So, the enactment of such equilibrium achievements has been assessed for cluster-based routing algorithms design in order to consider whether a good quality of network operation ensured.

Finally, we have quantified the overall efficiency of these algorithms by using standard networking evaluation metrics. So, the performance evaluations of our algorithms have been conducted in comparison with other algorithms (i.e., LEACH [5] and CROSS [14]) by considering the virtual reality of network deployments. Regarding the conducted simulation of our algorithms, it is observed that energy consumption has been balanced and distributed uniformly. Thus, network lifetime is much extended to provide a better packet throughput services.

1.2 Terminologies

Non-cooperative Sensor Nodes: [17] has given the following definition of selfish nodes: “As sensors may be owned and supported by different stakeholders, the authors view them as selfish agents maximizing their own network utility by exploiting other nodes’ resources.” It has been considered that individual nodes would unselfishly sacrifice their communication resources by relaying the message of the other nodes that only belong to the same stakeholders.

The same definition of non-cooperativeness has been employed in this dissertation as of [17], [18], [19], [20], [21], [22]. In this context, resource-limited nodes act selfish behavior with their

objective of utilizing the services provided by other networks while in the return, they behave unwillingness. In addition, in [17], the justification of these nodes is reinforced by the fact that nodes often have very limited localization capability in their resources in the deployed field. This happens typically because nodes either inaccurately read the signal due to the reason of environmental factors or initially they are designed with low-cost, and thus, are intended to save their resources. Storing the topology of the entire authorities' network information at the central point appears to be impossible and the nodes' control regime is also decentralized. Consequently, they must determine with whom they need to share their resources.

According to [27], the degree of network cooperation is affected by networking related external factors such as the number of available network domains, the density of nodes, the deployment area of networks and their topological arrangement, the location of BS, and the environmental propagating signal. Due to such factors, the intermediate nodes might misbehave by not forwarding the packets to other remote nodes. Sensor nodes are misbehaving in the cluster-based routing algorithm of a MWSN by minimizing their contribution to other nodes [14], [15]. In [52], it is stated that node selfishly acts in the cluster-based algorithm either by not participating in the process of CH selection or by not forwarding packets of its members, though it is selected.

In [35], [36] selfish node initializes the size of its contention window to a lower value than the normal cases. This node deliberately deviates from the Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) protocol. By so doing, a selfish node (also said to be a cheater node) increases its throughputs. In [38] selfish node also called "Greedy Node" is studied as the problem that occurs in the intermediation of multipath routing: node may turn off its power when it does not have active communications, node may not forward the packet it received, node may selectively send some packets while dropping others, and node may not forward the reply to the request on reverse route.

According to [23], selfish nodes are identified, they have the patterns: to avoid being included in the others' routes path, do not Relay Route Request (RREQ) messages, may not reply or transmit HELLO messages, deliberately delay the RREQ packet by exceeding the upper limit timeout, and may be part of the routing message, however, do not send the packets of others.

In synthesis, by taking into account everything about selfish agents, nodes that are investigated and modeled in this dissertation are classified as misbehaving ones. This kind of nodes hesitates the consumption of their own resources for the advantage of other networks. Henceforth, they are different from the class of nodes that deliberately misroute the data packets by falsely injecting. Misbehaving nodes have no intention to disrupt a usual network operation rather they do so to exploit the collaborators' resources. Conversely, they are unwilling to share their communication resources with others in return. In such configured networks, these nodes mostly drop the packets instead of forwarding. Such a misbehaving node is said to be selfish node otherwise known as non-cooperative node [17], [18], [19], [20].

On the contrary, there are other kinds of nodes that can inject false packets into the communication packets. By so doing, they misroute the packets of other nodes. Regarding this point, it is possible to pinpoint that the malicious nodes whose purpose is to disrupt the functionalities of other nodes either by impersonating or by attacking [53], [54]. Damaging the other nodes' normal operation, by causing network outage through partitioning, is among the many targets of these malicious nodes. Also, they may aim to consume the sensitive information about other nodes. Likewise, they are sometimes said to be active attackers [54], [55], [56], [57], [58], [59]. Mostly, these attackers are not driven by the intention of saving their resources, and due to this, they are not part of current studies.

1.3 Motivations of this Dissertation

In recent years, the sensor network field has witnessed a tremendous growth in terms of network's connectivity and applications that have attracted more users. The smartest sensor nodes, that made this network, have the ability to interconnect ubiquitously. This provides an opportunity for these nodes to gather information from everywhere at any times. Hence, this network has improved people's lifestyles by keeping them more connected to timely needed information. However, these nodes have limited resource capabilities which could restrict their functional quality and duration unless they are given due attention during their communication design. Correspondingly, the capability of how much the data packets they collect and transmit is largely predetermined by their limited amount of battery storage. Mostly, they consume more energy when transmitting the packets that they have been collected or sensed.

Research has made it evident that nodes misbehave as they tend to use their resources only for themselves. To curb such a challenge, recent research efforts are oriented towards the designing of efficient algorithms: they are expected to maximize the battery utilization of individually-owned nodes. One way of using the available resources efficiently to increase the network lifespan is to exploit the redundancy provided by the presence of multiple networks in the same area. In this regard, nodes that belong to one network accept to forward the packets produced by another, and on a reciprocally. Moreover, by standardizing the communication interfaces between these collocated nodes: it is possible to design the required collaboration even if they perform different tasks or belong to different owners.

This standardization could enhance the resource utilization in which case individual node correspondingly receives the advantages. In due process, the entire collocated networks should be expected to conserve their energy: eg., in [18], [27], network lifetime is sustained when the networks cooperate than not. As such, they deliver a comprehensive service for their respective domains with the remaining infrastructures. Thus, bringing up these nodes into a collaborative operation and designing an energy-efficient algorithm has been the motive behind this study.

Hence, this dissertation is meant to put forward an approach for designing an algorithm whereby the surrounded ESS can be achieved between non-aligned nodes. Indeed, a demanding challenge is how to design an effective model that regulates the strategic updates of mutual collaborative nodes. An individual node can dynamically update and adjust its strategy, in which acceptably entire nodes reach to share a common benefit.

Provided that equilibrium stability is achieved, an efficient algorithm has to be adopted. Thus, the best way is to design a cluster-based routing algorithm which conserves resource powerfully. This algorithm operates in two phases [7], [8]: the preparation of grouping nodes into clusters, called clustering-phase, and the routing-phase where the packet is collected, summarized and routed. In the clustering-phase, efficient methods are utilized to determine a CH, and organize nodes into different clusters. In the routing-phase, the determined CH is becoming a representative to aggregate and communicate the packet it received. As a result, it avoids an ordinary node from sending packets in the far distance. If the role of a CH is fairly distributed and rotated between these nodes, this technique anticipates many advantages: (i) it reduces the total transmission power; (ii) it can reduce redundancy by aggregating data; (iii) it

balances power exhaustion among nodes; (iv) it makes bandwidth utilization more efficient; (v) it increases the manageability and scalability of the network and (vi) it reduces routing and topology maintenance overhead.

Nevertheless, the classic cluster-based algorithms that deal with selfishness have several drawbacks with regard to the dissertation's motivation. Addressing this issue in the clustering-phase is considered in the present work.

1.4 Statement of the Problem

Founding the cooperation between individually-owned nodes in designing a cluster-based routing is the most significant requirement for the networks to operate effectively. Selfishness is one of the key problems that recently confronts the implementations of available algorithms (it is the case to LEACH [5], HEED [13] and etc.).

Regarding to these algorithms, a CH node has obviously a massive workload in comparison with other ordinary nodes. Thus, fairness dictates that the role of a CH has to be taken in turn by each node (if it is fit for that role); nevertheless, selfish agent (or node) refrains from CH selection. This node will like to skip itself by intentionally adopting several misbehaving characters: it can make itself unavailable for the role of CH, or, when in that role, can avoid relaying packets. If nodes widely adopt such characters, a considerable amount of energy is exhausted, which might affect the communication of the whole networks. Thus, the influence of nodes' behaviors in limiting the performances of the algorithm in combination with the fact that nodes are battery-operated motivates the need for an efficient resource allocation scheme.

Capturing the behaviors of these nodes in the algorithm design is the research problem to be addressed. Subsequently, this phenomenon adds another challenge into the domain of cluster-based routing algorithm that needs an immediate solution. Indeed, a new method of determining CH nodes - that takes into account the selfish nature of some nodes - is an inspiration to undertake this study.

The research works conducted so far have their own shortcomings in mitigating selfishness as well as in algorithm design. Owing to this, it is impossible for individual nodes to compute the Shapley value in [60], [61], [62], again in [14], [15], [16], [63], [64], [65], [66], [67], [68], [69], [70], [71] the assumptions of classical GT approaches (viz. complete knowledge about the

game, complete information of opponents' type, and full rationality of nodes') which are inappropriate to implement in the WSN settings [20], [22]. Moreover, energy consumption has squarely increased in the course of cluster formation in [67], [68], [70], [71].

Another key technical problem encountered can be attributed to the procedure of CH selections [14], [15]. Regardless of its current energy level, any node is randomly considered in order to represent its member nodes, in such scenario; the node with minimum energy level may soon get exhausted (and stops its functionality). As a result, these algorithms failed to solve the myth of the trade-off between extending the individual nodes as well as that of the entire networks lifetime. Consequently, network communication lacks the scalability and robustness to deliver user expectations in packet throughputs.

Thus, in this study, we intend to overcome such a challenge by adopting EGT as a sounder model so as to manage the mutual collaborative achievement of all collocated nodes. In this regard, establishing a mechanism of stable equilibrium which is important to sustain the network operations has been analyzed. Then, we propose an algorithm that intends to minimize the effect of misbehaving nodes in terms of resource utilization. Considering the aim of design, the performance overheads should also be taken into account since we are dealing with resource-limited sensor nodes after all. As such, energy utilization is the key attribute in which our algorithm has to be carefully managed. In this setting, guaranteeing fair spatial dispersion, rotating CHs, and balancing communication energy between individual nodes within the network will be the proposed solution.

Therefore, designing an appropriate CH-determination algorithm has been considered with respect to harmonizing the role of individual nodes in the course of packet routing. In this regard, determining a node which has a better performance as a CH role and organizing the remaining nodes into a number of balanced clusters has been found crucial in due process. The proposed algorithm can extend the network lifetime with regard to delivering enhanced packet throughputs.

1.5 Research Objective

General Objective: This dissertation intends to model an evolutionary collaborative achievement in the MWSNs, and thereby proposing an energy-efficient cluster-based routing algorithm which can extend the network lifetime.

Specifically, this dissertation was set to achieve the following objectives:

- To model the behaviors of non-collaborative nodes so as to achieve a stable equilibrium strategy.
- To propose CH-determination algorithm which determines, fairly rotates, and distributes the CH roles.
- To evaluate an energy-efficient cluster-based routing algorithm where collaborative network operations are ensured to extend the network lifetime.

1.6 Research Methodology

The method adopted to achieve the objectives of this research is summarized as follows:

- i. Literatures Survey in the Area
 - Relevant literature on WSNs and cluster-based routing algorithms in MWSNs has been reviewed.
 - The related works around our research challenges have been critically reviewed.
 - In addressing the behaviors of selfish nodes, the available techniques have been investigated, in which the appropriate one is identified.
 - The possible procedure to design a cluster-based routing algorithm has been considered.
- ii. We have developed an ECG in order to model the behavior of nodes. We have defined ECG model by assuming: node as a player, which admits a strategy of either collaborates or non-collaborates to get some benefits in packet transmitting. Thus, we assumed EGT approaches into our model where nodes engage with other population of nodes by assessing the advantages they received.

Then, as per nodes' population dynamics, we have studied replicator dynamics in accordance with strategic interactions of nodes. First we studied an ECG model that focused on two-player interactions of a pair-wise contest game and then, generalized for a population game of Multi-players Contest Game (MCG) - the interaction of nodes is either globally or

locally. We have also introduced a rewarding mechanism for the improvement of collaborative equilibrium since a large number of nodes globally interacts.

As such, the dynamic equations have systematically been developed to assess the stability achievement of nodes' behaviors. We have considered – both in the analytic model and in the simulation – the worst case scenario, where each node belongs to a distinct authority or agency. In this context, collaborative equilibrium achievement has been worked out analytically for a small number of nodes and numerically for a very large number of nodes. Then, the representation of equilibrium behaviors has been analyzed and discussed in accordance with the payoff parameters (i.e., w and d) and the number of N nodes (see Section 4.4 and 5.2).

- iii. Then, we have proposed two cluster-based routing algorithms (CPF and GREET algorithms) as per collaborative equilibrium achievement of our ECG model. First we have proposed CPF algorithm along with the equilibrium probability (i.e., an incentive-based global collaborative equilibrium) that has been achieved in the course of nodes' interactions. By computing a cooperative-rate of nodes, a potential node is rotated by a CH-determination algorithm so that its performance is also compared with the default cases (NcPF algorithm): nodes were realized to be misbehaving (see Section 4.5). Then, by extending the analytic model of CPF, a more relevant assumption about the competition of nodes has been considered (i.e., in the proposed GREET algorithm, locally nodes share their information).
- iv. An evolutionary cluster-game has been adopted so as to achieve the equilibrium collaboration between neighboring nodes. The latter cluster-based algorithm has been introduced as such when the CH-enabled nodes will be contested to determine whether to bid for CH candidate or not. The detailed phases of GREET algorithm development have been described in Section 5.3.
- v. Lastly, we have conducted simulation and assessment
 - Simulation: MATLAB-based simulations have been carried out to study our proposed algorithms. Through evaluating the dynamic equilibrium achievement of our analytic model, then, the applicability of our algorithms has been assessed in a realistic context. MATLAB version 7.12 (its released name R2011a) has been considered. Full detail about MATLAB discussion has been presented in Section 6.2.

- **Network Evaluation Metrics:** The suitable network metrics that describe the enactment of our algorithms have been identified to drive the conclusion. Accordingly, the network performance evaluation criteria such as network lifetime, residual energy of nodes, and packet throughput were studied in order to demonstrate the achievements of our cluster-based routing algorithms.
- **Assessment:** The assessment of our newly proposed cluster-based routing algorithms has been conducted along with other standard algorithms such as LEACH [5] and CROSS [14]. Our simulation results have been analyzed and discussed in Section 6.3.

1.7 Organization of the Dissertation

The contents of this dissertation are organized into seven chapters: Chapter One is an introduction - provides a brief synopsis of the whole dissertation. The research subjects and the most relevant research works of the remaining chapters are outlined as follows.

Chapter Two introduces the concept of WSNs: characteristics, topologies, routing algorithms, and their classifications. Correspondingly, the discourse of cluster-based routing algorithm over the other routing algorithms is presented. The behaviors of selfish nodes and their effect on the network performance are discussed by focusing on cluster-based routing. GT approach is also discussed with an objective of analyzing an EGT. Then, GT approaches for designing WSNs applications are discussed. Chapter Three critically discusses the existing methods of mitigating the selfishness. The detailed individual schemes of cooperative packet forwarding and cluster-based routing algorithm in the context of the selfishness are debated.

Chapter Four illustrates the achievements of collaborative network operation in WSNs where initially nodes do not cooperate. ECG model is developed and its theoretical aspect is also discussed. In addition, the replicator equation is analyzed by considering the interaction of nodes in population game, and its stable state is investigated by introducing a mechanism of rewarding; and the behaviors of stable equilibrium are studied analytically. For a large number of nodes, it is also studied numerically using simulation. Lastly, the packet forwarding scheme is proposed and evaluated in accordance with cluster-based CPF and NcPF algorithms.

In Chapter Five, the model of extended ECG is considered by restricting the interaction of nodes' inside the cluster. As a result, the analytic evolutionary cluster-game (M-node game) is

formalized and its stable equilibrium is studied for neighboring nodes. Using numerical simulation, the achievement of equilibrium validation is also provided. As such, the detailed development of GREET algorithm is discussed, which is followed by a presented theoretical assessment. Chapter Six presents simulation-based performance evaluations. It provides a significant insight into the basic properties of our proposed algorithms in more realistic scenarios by introducing evaluation metrics as well. Chapter Seven summarizes the research results, and contributions made in this dissertation in addition to highlighting the possible future works. Lastly, the bibliography is presented and followed by the Appendixes Section which presents some examples to show the effect of selfishness on the network performances.

CHAPTER TWO: LITERATURE REVIEW

This chapter introduces WSNs by taking into account the challenge of selfish nodes' behaviors in the multi-class network design and GT, which plays a critical role in the dissertation's solution approach.

The chapter has five different subsections: Section 2.1 presents WSNs along with their characteristics, applications, topologies, and the different types of routing algorithms. In Section 2.2, the mechanism of conserving the communication energy in cluster-based routing algorithm is discussed. The concept of GT strategy is introduced in Section 2.3, while the concept of evolutionary population game is discussed in Section 2.4. The role of GT in designing WSNs is also assessed in Section 2.5. Finally, the summary of the chapter is provided in Section 2.6.

2.1 Overview of WSNs

This section briefly describes WSN, its characteristics, topologies, routing algorithms, and their classifications. WSNs have been recognized as one of the emerging innovative technologies. This is because it brings the interaction between humans and the surroundings to a new level of information diffusion. Although a significant progress has been made in the field of WSNs, the existing technology development needs a lot of improvement. In this case, research in sensor networking is showing a rapid and tremendous evolution [3], [4], [72]. Since WSNs provide ubiquitous connectivity without the need for real infrastructure, their application is very attractive in today's real-time information requirements.

WSNs are composed of a large number of low-power multi-functioning nodes operating in an unattended area with limited computational and sensing capabilities [1], [2], [72]. In addition, these networks have diverse connectivity for the nodes that belong to different users can be randomly positioned and managed [17], [18], [19], [20]. These small-sized and inexpensive devices can sense, measure, and gather information from the environment based on some local decision processes. To perform these activities, nodes are scattered in a region where they collect the data through their sensing antennas. The collected information is then forwarded to other connected nodes in the network (assume a BS). The BS, in turn, sends an updated result

back to each node. In short, a sensor node is a device that is capable of collecting, processing and communicating some sensory information to the end user through a BS [1], [4].

In most WSN application scenarios, the location of sensing nodes is far from the destination of BS (also called sink). As a result, the packets sent between distant nodes are expected to be relayed by intermediate nodes that might act as routers by providing packet forwarding service. That means, the packet of a remote node expected reaches the intended destination through the intermediated nodes. So the communication is assumed to be successful depending on the behavior of such intermediates. However, the collocated nodes might be refused to provide such services since their purpose is to save their resources [17], [18], [19], [20], [21]. Moreover, as their capacities such as energy, storage space, and computational capability are limited, nodes may intend to obtain a much larger share of network bandwidth at the expense of other users' networks. In due process, they indirectly affect the network: QoS is reduced when these nodes fail in forwarding packets [23], [24], [26]. To overcome this problem, a reliable and energy-efficient cooperative routing algorithm is required.

The problem of misbehaving nodes toward packet forwarding is a very common phenomenon in the distributed wireless networks [73], [74]. User expectation may never be realized in these multiple networks since some of the nodes may prefer to drop the other nodes' packets. In order to ensure proper functioning of such networked schemes, designing a mechanism which enables cooperation between nodes is very important. The attainment of cooperation in wireless ad hoc networks has been addressed in [46], [75], [76], [77]. These authors assumed that node has the capability of acting rationally though its action is strictly determined by its computation. However, due to the characteristics of WSNs, their cooperative design has differently been addressed [20], [22].

2.1.1 Characteristics of WSNs

There are networks that are deployed in ad hoc manner. These are Wireless Mesh Networks (WMNs), Wireless Sensor Networks (WSNs) and Mobile Ad hoc NETWORKS (MANETs) [1], [2], [78]. Contrary to WMNs, WSNs and MANETS are deployed without the necessity of using any pre-existing infrastructure for computation and communication of data packets. Nodes in WSNs and MANETs are connected to each other through wireless communication links and they have dynamic network topology. Nodes in both WSNs and MANETs have limited

communication resources. On the other hand, WSNs and MANETs are ultimately different due to the fact that MANETs typically consist of deployed nodes that are designed for a distributed computing whereas sensor nodes in WSNs are typically deployed in certain sensing regions to collect information. The cost of individual nodes in WSNs is cheaper than that of nodes in a MANET. Unlike MANETs, WSNs contain a large number of nodes. Sensor nodes have much more limited power, computational and communication capabilities than those of MANETs.

An individual node has the ability to sense, collect and process information depending on its hardware components. Obviously, these components are interrelated to facilitate the functional activities of sensor nodes. Within a typical node, there are four distinct units or components that are assigned to manage different tasks [1], [2], [3], [78]. These components are sensing unit, processing unit, transmission unit, and power unit.

- i. **The sensing unit:** is responsible for sensing a phenomenon. Usually, it is composed of two sub-units: the sensor which produces the analog signal by sensing the physical environment, and the analog to digital converter which transforms the signal into digital signal and feeds into the processing unit. Depending on the application of sensor network, the type of sensor being embedded into a node may include target tracking, wildlife monitoring, structural monitoring, pollution studies, and surveillance.
- ii. **The processing unit:** is responsible for tasks such as scheduling, data processing, managing and controlling the functionality of other components in the node.
- iii. **The transmission unit:** connects the node to neighbors so that communication takes place between them. Usually it has a radio transceiver that has the combination of both a transmitter and a receiver. Hence, it is liable for transmitting and receiving data to or from other surrounding nodes or a BS.
- iv. **The power unit:** has the responsibility to supply power to the entire nodes' components.

Optionally, depending on their application, the hardware of sensors may be equipped with additional components such as a location finding system and a mobilizer.

In general, WSNs are characterized by the following features [1], [2], [3], [4], [72]: (1) the network relies on a collection of tiny sensors to observe the real world; (2) nodes are acutely limited in energy, computation, and storage capacities; (3) nodes have a modest and sometimes non-renewable battery power; (4) there is no real infrastructure in WSN; (5) nodes are self-

organized, self-configured, and self-optimized network schemes; (6) their network topology changes dynamically; (7) most of sensor networking applications consider many-to-one data traffic pattern, i.e., the data sensed by individual nodes flow from multiple source nodes to a particular destination (expecting that nodes work together); (8) nodes are densely deployed in a region of interest, as a result, redundant data might reach the destination; and (9) due to a large number of nodes deployment, it is usually not possible to build a global addressing scheme for a sensor network (no global identification).

2.1.2 Applications of WSNs

WSNs are deployed everywhere, such as on land, underground, and underwater [4]. These wide deployments happen due to the fact that this network has a short system set up time; and nodes can be deployed ubiquitously, relatively with affordable operational cost. These nodes sense and gather different raw data and their applications are very broad. Depending on the characteristics and requirements of a system, such applications can be possibly grouped into monitoring and tracking [1], [3], [4]. Monitoring applications include environmental, health, inventory location and structural while tracking applications include objects, animals, humans, vehicles, and enemy.

Its versatility and broad range of applications are attracting the interest of both the research and the industrial community [78], [79], [80]. As a result, much attention has been given to designing a routing algorithm since packets gathering and routing might differ depending on the application and network architecture. In this case, multi-domain networks that are deployed to sense different applications might be cooperated in routing to improve their performance (eg., network lifetime extended [27], [112], [113]); otherwise, it results in network degradation, reduction of network lifetime, deterioration of QoS and etc. [23], [24].

2.1.3 Topology of WSNs

In order to ensure the effectiveness of packet delivery, the network connectivity must be guaranteed by adjusting the transmission power of each node [2], [4]. The internal resources constraints of nodes such as transmission power and energy level are considered in addition to the other environmental factors such as nodes' deployment schemes and locations to establish

their topology. Topology control is an issue in WSN since it plays a central role in the interconnection of the network [81], [82].

The topological representations of WSNs are classified into four types and these are shown in Figures 2.1a, 2.1b, 2.1c and 2.1d [81]. These are single-hop and multi-hop flat models; single-hop and multi-hop clustering models. In the case of single-hop, all nodes transmit their data directly to the BS; while in multi-hop nodes transmit their packets through their neighbors, as shown in Figures 2.1a and 2.1b. In large scale area of network architectures, single-hop is infeasible because the cost of transmission to a long distance is expensive in terms of energy utilization, and the BS may even be unreachable in the worst case. In the multi-hop flat model, all nodes share the same information such as routing tables for transmitting the data packets to the BS, thus, communication overhead and energy consumption might be increased.

In the clustering model, nodes form a group and select one potential node to communicate with the BS. The selected node aggregates redundant packets when transmitting, and hence nodes maintain low overhead and energy consumption. In clustering model, if nodes reach a BS in one hop, it is said to be single-hop clustering; otherwise, the clustering is said to be multi-hop since nodes reach the BS in multi-hop transmission, as shown in Figures 2.1c and 2.1d. Therefore, cluster-based topology arrangement has widely been accepted as an effective method of designing energy efficient, robust, scalable and distributed networks [7], [80], [81].

2.1.4 Routing Algorithms

Sensor nodes have to use their neighbors in order to route their sensed data packets. In this case, before eventually reaching the intended destination station, the packets in transit have to pass through several intermediate nodes. Thus, routing techniques are required for sending packets between source and destination nodes [4], [72], [83].

A. Considering in Designing the Routing Algorithm

Designing an efficient routing algorithm is an important issue in resource-limited WSNs. There are several metrics to be considered in designing a suitable path, and some these include energy consumption, scalability, topological arrangement, and application [1], [2], [4], [7]. WSNs are off-grid, unlike energetic networks designs. These means that nodes have limited energy storage, so efficient energy utilization is the key factor for extending network lifetime. The

reduced lifetime of the network will affect the qualities of packet communications. In other words, if the energy of a node is not properly managed, some of the nodes would die early which might further disconnect the network. As a result, it is difficult to provide effective operation and seamless coverage in the network application.

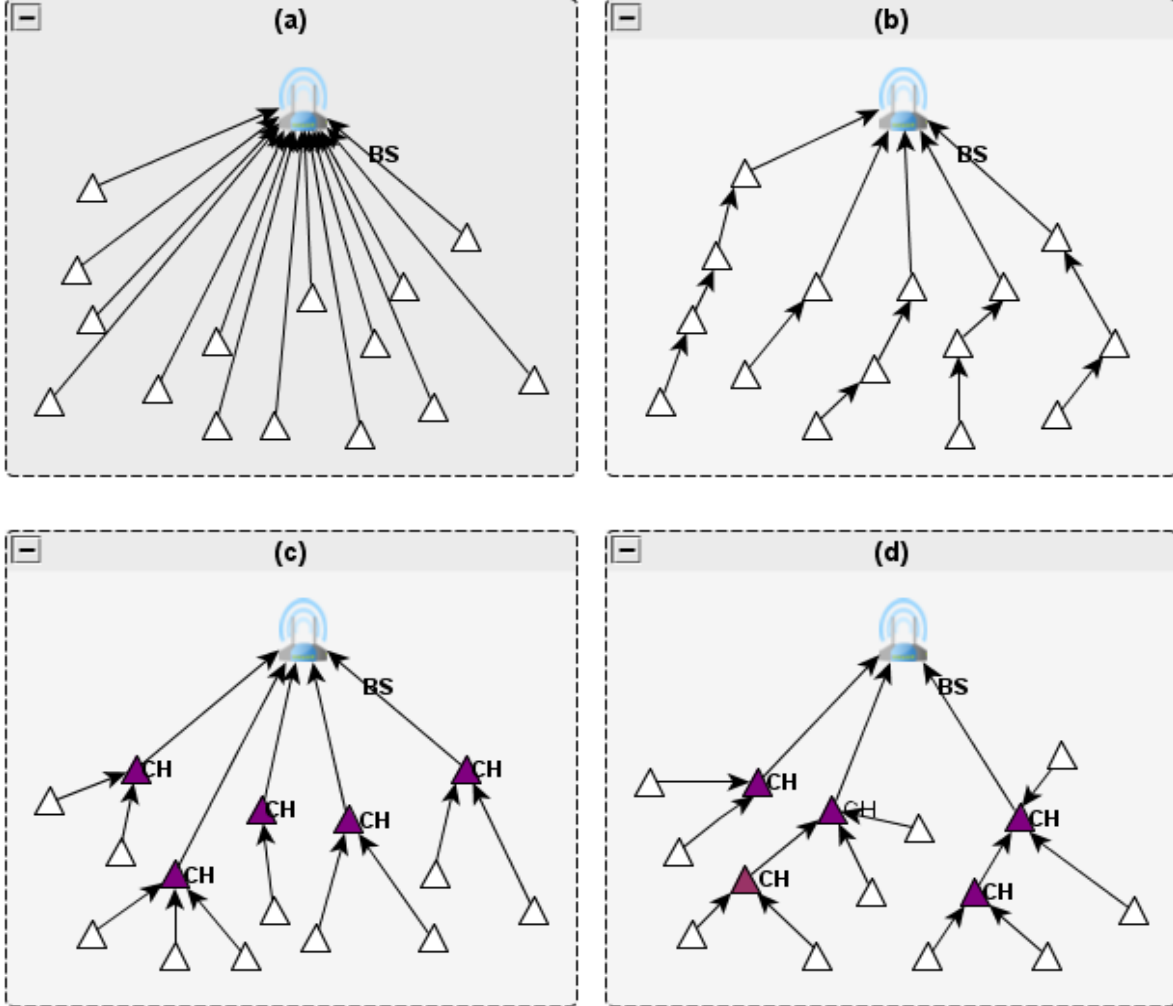


Figure 2.1: The General Topological Representations of WSNs: (a) Single-hop Flat Model; (b) Multi-hop Flat Model; (c) Single-hop Clustering Model; and (d) Multi-hop Clustering Model

Designing the routing algorithm for sensor networks is a challenging when compared with other wireless communication networks [1], [3], [84]. Firstly, contrary to other typical wireless networks, sensor network supports many-to-one communication. Secondly, building a global addressing scheme such as Internet Protocol (IP) address is unthinkable for a large number of nodes available since it brings communication overheads. Thirdly, since nodes are randomly

deployed in most applications, there is a possibility of having different nodes in the same vicinity that can sense and generate the same raw data. In order to effectively utilize bandwidth and energy resources, routing must avoid redundancy in transmission. Fourthly, nodes have limited resources such as onboard energy that need to be carefully managed [2], [4], [72].

Hence, in designing the path for packet transmission, one has to consider the landscaped feasibility between networks. This is to say that routing algorithm of WSNs has to be designed in a different way compared to other communication networks. In order to provide better service, because the application domains and methods of sensor networks deployment are decisive. Besides these metrics, what makes designing a routing algorithm more challenging is the behaviors of collocated nodes. In the course of the nodes deployment, the assumption of cooperation between them would be imperfect due to its limited resources. That means they want to save their resources (such as battery power and CPU cycles) and this violates the normal routing algorithm by adopting different strategies such as selfishness [14], [15], [17], [63], [85]. Thus, a routing design must consider the behavior of these nodes.

B. Taxonomy of Routing Algorithms

Routing algorithms of WSNs are classified into different types [3], [78], [83]. Their classification has been determined by various network parameters and these include mode of targeted applications, participation style of nodes, and network structures, as indicated in Figure 2.2. Thus, considering the mode of nodes functioning and the types of targeted applications, the routing algorithms can be classified as proactive, reactive and hybrid. In a proactive routing algorithm, nodes sense the environment and transmit the data to a BS through a predefined route. On the other hand, if there are sudden changes in the sensed attribute that would be reached beyond some pre-determined threshold value and that the nodes immediately react as such the algorithm is said to be reactive. The hybrid routing algorithms are designed with the objective of incorporating the concepts of both algorithms.

Routing algorithms of WSNs can also be classified according to the method of nodes' participation [83] and this includes (i) Direct Communication - any node can sense and send its information directly to the BS; (ii) Flat Communication - node searches for a valid route to the BS and transmits the data, and (iii) Cluster-based Routing Algorithm - the total area of nodes' location is divided into clusters and each cluster has a CH as shown in Figures 2.1c and 2.1d.

Individual nodes transmit the collected data to a CH and then, CH aggregates the collected data packets and forwards to the BS.

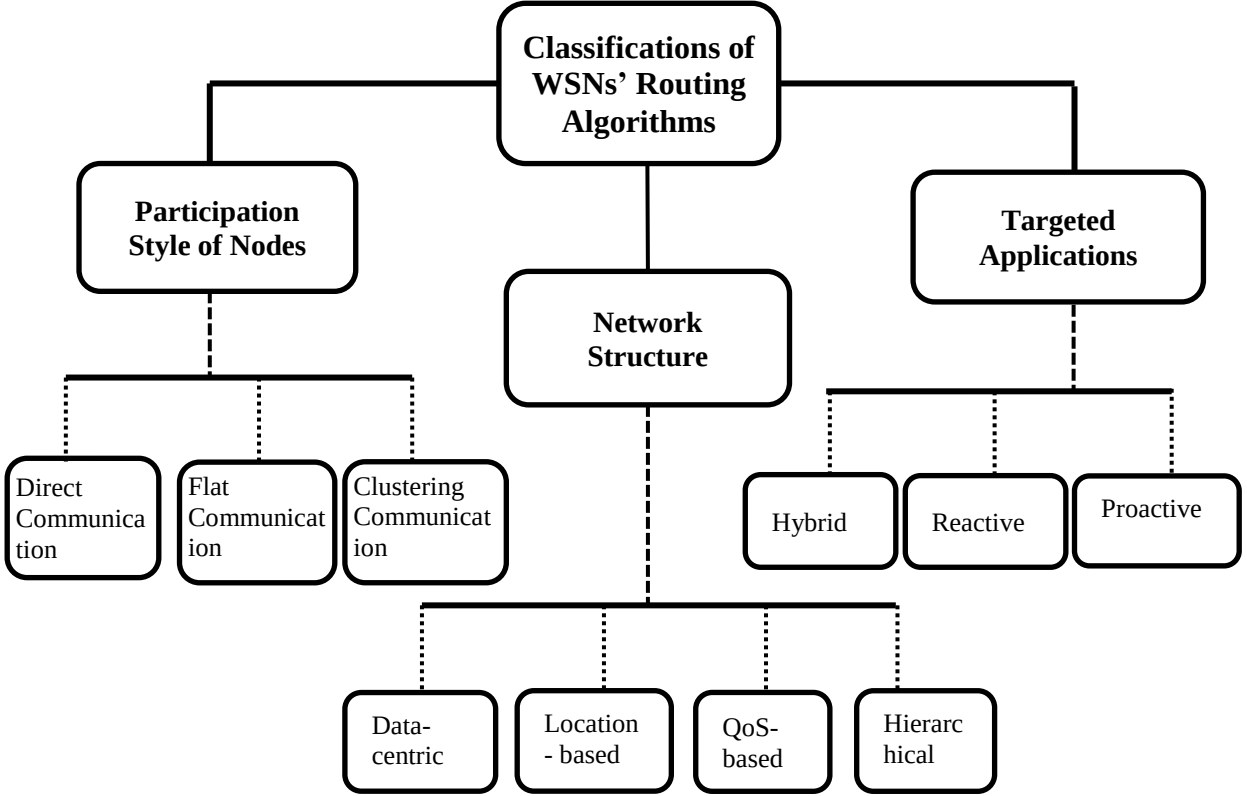


Figure 2.2: Taxonomy of Routing Algorithms in WSNs

Furthermore, according to the network structure, routing algorithms can be classified as Data-centric (Flat Architecture), Location-based, Quality of Service (QoS)-based and Hierarchical (Cluster-based) [3], [78], [83].

- i. **Data-centric Routing Algorithms:** these types of algorithms distribute the information needed to any reachable nodes [3], [78]. No effort is made to organize the network or its traffic and the intention is only to discover the best route in hop-by-hop to transmit the data to a destination. In these algorithms, all nodes play the same role and there is no absolute hierarchy. Data-centric algorithms such as flooding and gossiping consume more energy and nodes located near the BS transfer more information than nodes located in other parts. As such, these types of algorithms suffered by data overload or congestion. As a result, sensors die faster and this, in turn, creates a disconnection between the BS and the WSN.

Consequently, these algorithms result to an uneven energy consumption in the network and limit the scalability of the network.

- ii. Location-based Routing Algorithms:** most of these algorithms require the distance between sender and receiver nodes [3], [84]. Their information might be used in order to estimate energy consumption. Thus, to provide the information about their location, GPS has to be integrated into the embedded board of each node. Yet, including the GPS into sensor nodes is not applicable in many aspects as it consumes too much energy.
- iii. QoS-based Routing Algorithms:** these routing algorithms consider delivering a better QoS as additional metrics in their designing [78], [86]. These provide additional capabilities to WSNs, where more sophisticated applications can be developed and improved. In particular, multimedia communication necessitates other performance metrics such as throughput, delay, and jitter to be considered in designing. Meanwhile, in some situations, delay may be even more important than energy consumption. Thus, the QoS requirements of such applications need to be guaranteed in addition to energy efficiency. However, providing additional assurances obviously increase the cost in terms of energy and, hence, reduced network lifetime. The trade-off between these additional capabilities and their costs should carefully be weighed in accordance with the applications.
- iv. Hierarchical (Cluster-based) Routing Algorithms:** these algorithms attempt to arrange nodes hierarchically into different groups, as shown in Figures 2.1c and 2.1d. The role of nodes should be either CH or member nodes. When nodes are organized in a hierarchical structure, their divisions into the clusters form a hierarchy of layers. The CH would be selected for each cluster in the hierarchy where such CHs can also form a hierarchy with others which could represent multi-hop data transmission. In these aspects, packets coming from the CHs located at a far distance might pass through the others (CH-to-CH) before reaching the intended BS.

As a local coordinator, the CH performs data aggregation (fusion) in order to decrease the number of transmitted packets in the case of redundancy. By so doing, energy of an individual node could be conserved, in which case the service duration that is provided by the network should be sustained. In short, in order to enhance the network lifetime, cluster-based algorithm plays an important role in providing efficient communication since the network is also scalable [7], [8].

This algorithm is initiated by a **clustering-phase** (also called **set-up phase**) which is followed by the **routing-phase**. Both phases successively compose one round of an algorithm for dispatching packets. Actually, the rounds increment and iterate throughout the network's lifetime. **CH selection and cluster formation** are the two activities in the clustering-phase: the former is the first step to initiate this algorithm when nodes prompt to serve their member nodes as a CH, (assume they are cooperative). The latter one starts when CHs broadcast advertisement messages to their neighboring nodes. Once the other non-CH nodes hear this announcement message, they request to join the CH in their surroundings. Then, CH assigns a time slot for its member nodes (i.e., nodes that are in the same cluster) to transmit their packets. The other activities are **data aggregation and transmission** which are performed during the **routing-phase**. Data aggregation is the process by which the CH combines similar data packets coming from its member nodes while data transmission or communication will be materialized in the course of data packet transmitting.

2.2 Communication Energy Preservation

As sensor nodes are battery-operated, preserving their communication energy is the most important challenge to extend their functionalities. A tiny sensor node uses battery power as its source of energy. Their deployments can be sometimes in hazards environments where either changing the batteries or providing energy is difficult. Data sensing, processing, and transmitting are the major operations of nodes; however, data transmission consumes the largest amount of energy. For these purposes, an energy-efficient communication is always demanded to sustain the services of a sensor network. Among the plenty of methods discussed, clustering neighboring nodes are the most popular solution [5], [7], [8], [13].

2.2.1 Cluster-Based Routing Algorithm

As discussed in the previous section, this algorithm arranges the nodes into various clusters; accordingly the nodes that have high energies are arbitrarily selected for packets processing and sending while nodes that have low energies are used for the purpose of sensing and sending the information to the CHs. Then, CH transmits the summary of aggregated data packets and this process helps the network to optimize its communication bandwidth. Obviously, this process

has the advantage of saving energy effectively; it has the capability of extending each node's lifetime and it contributes to the scalability of a network [87], [88], [89], [90], [91], [92].

The application of a sensor network might determine the method of packets communication [1], [2], [4], [72], [78]. Routing algorithms are application specific. In some sensor network applications such as monitoring, for instance, the raw data that are sensed by nodes' flow from different source nodes to a single BS (i.e., the flows of traffic exhibit a many-to-one pattern). In this regard, grouping those nodes into a cluster is much better than the other routing methods. Accordingly, resource-constrained nodes need to send their raw data only to their nearest CH instead of a very far distance BS. So, the signal interference that might occur at a physical layer and the collusion of the packets would be minimized since the packets of nodes in the same cluster are sent through a single CH [1], [72]. Consequently, cluster-based algorithms are widely considered in maintaining the network topology [7], [81], [82].

In hostile areas, deploying nodes in a pre-planned manner is impossible [93]. Rather, thousands of nodes are randomly placed or dropped (i.e., a possibility of finding multiple nodes in the same sensing field). In such an environment, neighboring nodes might sense and gather the same phenomena, and transmit data packets redundantly. They would waste communication bandwidth and consume their crucial energy unnecessarily. Yet, such problems would be easily resolved if a cluster-based algorithm is employed. A number of clustering methods (such as rotating the workload of CH, optimal clusters division, etc.) are also incorporated to conserve energy resources [7], [8], [94], [95].

Considering the advantages of this algorithm, many improvements have been made so that the functionalities of individual nodes can be extended [14], [15], [16], [91], [92]. Fundamentally, nodes are assumed to assist one another in establishing and routing that keeps the network alive. In spite of the common advantages, individual nodes might misbehave which occurs when they utilize resources alone. This leads to separately adopting unwillingness toward sharing CH workload. Taking the behaviors of nodes, cluster-based algorithms would be characterized as clustering schemes with cooperative nodes [7], [91], [92], [96], and clustering schemes with non-cooperative nodes [14], [15], [16].

A. Clustering Schemes with Cooperative Nodes

In this type of cluster-based routing schemes, nodes behave cooperatively. They are assumed to act honestly toward the others, in which CH role is voluntarily alternated. In this scenario, these nodes can transmit the packets in cooperation for their common advantages and work in agreement to sacrifice their resources on behalf of other members. In view of these scenarios, several conventional routing algorithms were developed [5], [6], [9], [10], [11], [12], [13].

LEACH [5] is probably one of the first cluster-based routing protocols designed. It assumes that each node in the network is cooperative towards cluster establishment. CH is randomly self-elected and rotated in a probabilistic manner. This algorithm incorporates data fusion for first times, as such, it is also assumed as the foundation for many cluster-based algorithms. Since the early designing of this algorithm, enormous amount of researches have been conducted for its improvements [6], [9], [10], [11], [12], [13], [91], [97], [92], [87], [88], [89], [90]. Their main objectives are alleviating the communication energies by advancing the clustering methods. The enhancements are made at different phases although majority of them focused on CH-selection techniques.

LEACH-C [6] has been proposed in order to overcome the limitation in LEACH clustering. It allows the participation of BS in the CH selection. For these purpose in every round, each node has to send its energy and location information to a BS. Then, the BS selects the potential CH and notifies the information of selection to every node. The BS has advanced computation capabilities and unlimited power for delivering the functions. However, the problem with the LEACH-C is its inability of using the characters of nodes self-organizing. Instead, the algorithm allows a BS to interfere in the process of CHs selection. This forces all nodes to communicate with a BS in every round to report their energy information as well as their location. This algorithm is also inefficient for very large networks.

PEGASIS [9] protocol is developed by constructing chains of nodes instead of clusters to address the overhead caused in clustering-phase of LEACH. The greedy algorithm is used to perform the construction of chains, where cooperative nodes select their closest neighbors as next hops in the chain. There is the assumption that the nodes have a global knowledge of the network and the chain construction starts from the nodes that are very far from the BS. As a result of chain operation, each node keeps track of its previous and next neighbor. Communication in the chain is performed sequentially so that each node within a chain

aggregates data from its neighbors until all data are aggregated at one of the last node (also called chain leader). This algorithm is inefficient because of its packets bottleneck that might happen at the chain leader. Also, considering a global knowledge about the network to initiate the construction of the chain might be impossible for nodes.

Another centralized cluster-based protocol, namely the BCDP is described in [10]. This routing protocol forms balanced clusters, where each cluster has the same number of members to avoid cluster overloading. The BCSP [11], on the other hand, aims at extending the network lifetime by basing the clustering decision on the remaining energy of every node. The BS redistributes the role of CH among the nodes from time to time. In this algorithm, the cooperative nodes send the information such as their energy and their location to the BS together with sensed data. The fact that CH selection is centrally managed in both protocols, they face similar limitations that occur in LEACH-C.

WCA [12] is an on-demand distributed algorithm that combines several properties in one parameter (weight) for clustering. The algorithm is executed only when a cooperative node is no longer able to attach itself to any of the existing CHs. This scheme considers multiple parameters: battery power, mobility, and the maximum number of cluster members and uses a weighted sum of the parameters in a combined metric that should be optimized. However, the additive character of its metric means that not all its parameters could be optimized simultaneously that a compromise among them needs to be made (i.e., its performance limited).

HEED [13] is another clustering method for ad hoc and sensor networks that is completely a distributed algorithm, and no assumption is made regarding the location knowledge of each cooperative node. CHs are randomly selected on the basis of their residual energy normalized by their initial energy. In addition, it can be combined with a metric that takes the node density into account. If nodes' initial energies are not identical, it has been proved that HEED performs better than the modified version of LEACH. However, as CHs need to communicate constantly with their neighbors, a redundant cost is produced by HEED thus affects the network lifetime.

An Energy Residue Aware (ERA) cluster-based algorithm is developed as an improvement of LEACH [91]. A path with maximum energy residue sum is associated with a CH selection in order to balance energy consumption of the entire networks. Unlike in LEACH, in ERA the entire network lifetime is extended, and also node has better remaining energy per round. CH-

selection optimization called LEACH-E [97] is developed based on the energy threshold of each node. The theoretic basis of computing the optimum number of CHs for the network is designed. To improve the randomized CH selection procedure in LEACH, CH selection probability and nodes' remainder energy is studied. Then, the node with high remaining energy is selected through increasing its probability of being a CH. Thus, the energy consumption and the network lifetime would be balanced.

EECS [92] is developed for periodical data gathering applications. To achieve a well uniform distribution of CHs across the networks through localizing radio communication, a node with more remaining energy is selected as a CH. During the CH selection phase, constant numbers of candidate nodes are selected. The nodes compete locally for CH by considering their residual energy with some iteration. In order to balance the CHs loads among the nodes, the weighted function cost is also introduced for the clustering-phase. With network lifetime, EECS performs better than LEACH. However, in EECS the global knowledge requirement about the distances between the CH and the BS might increase communications overhead. EECS has been extended into an unequal cluster-based routing protocol [95]. It has been developed according to the observation of a CH close to the BS consumes more energy on forwarding packets. Then, by grouping the nodes that are nearest to a BS into clusters of small size, the corresponding CHs utilize less energy for the purpose of communication. In that context, the power usage of an arbitrary CH is balanced regardless its distance from a BS.

Deterministic CH selection [87] is proposed for selecting the expected number of clusters in WSNs. This method overcomes the inefficiently CH selections in LEACH. The mathematical modeling is used to estimate the optimum number of clusters, based on the number of clusters with the network lifetime relationships. If k is the expected number of CHs nodes among N numbers of sensor nodes in each round, in every $\frac{N}{k}$ round, a node becomes CH once and non-CH at $\frac{N}{k} - 1$ at other times. In each round, the number of CHs is predefined based on the remaining energy of the sensor, and such technique gives a clear estimation of energy consumption. At every round of CH determinations, the model considers the energy exhausted by non-CHs and also the energy required for initiating clustering-phase.

The energy consumption in LEACH, as a result of repetitive clustering-phase, has been solved by the method of Round-Robin Cluster Header (RRCH) [88]. It selects the CH in a round-robin manner by fixing the cluster status. Only at once at the initial stage that CH formation is defined. Then, in the data schedule, every non-CH node receives a parameter value of {node_id, sequence}. So, according to the sequence number that corresponds to its node_id, the node carries out the role of a CH. As a result, the energy consumption would be balanced between the CH and non-CH nodes.

Learning based method also called rewarding based clustering algorithm is developed in [89]. This algorithm has two phases: cluster set-up and data flow phase. The cluster set-up is the first phase in the learning based method to determine the concerned CHs while the data flow phase is a long duration, in which the sensed data are transmitted. Thus, the algorithm starts by determining the CH node by calculating (i.e., the previous reward and residual energy of the node are considered) and comparing the reward of every node in the surrounding. The node that obtains a higher reward gets the priority to be a CH in order to form its cluster member by removing the other CHs with no members. Thus, the energy dissipation would be distributed evenly throughout the nodes.

The parameter of distance and current energy status of sensor nodes have been considered in the cluster-based algorithm in [90]. It estimates the available energy of each node in a round of transmission. The node with the maximum energy in the round would be selected as a CH. Then, the distance parameter would be considered for determining the cluster members. Thus, each node has been the member of a CH by estimating the distance it has from the currently selected CH and the distance of that CH from the BS. The Modifications in LEACH is also introduced [98]. It is another version of LEACH, where CH replacement technique and dual amplification are improved. In short, such collaborative assumptions work only for particular applications where all collocated nodes priorly reached a collaborative agreement.

B. Clustering Schemes with Non-cooperative Nodes

Sensor networks may be deployed in the common sensing region. These WSNs may be controlled and owned by different authorities or they may belong to the same owner but installed for different purposes [21], [22], [27]. Since their applications are manifolds, there is a possibility of such networks collocated in the same area. For instance, non-government

organizations use sensor network for the purposes: wild animal's surveillance and monitoring the natural environment around wild animals and their behavior in the forest. In the same vicinity, sensor networks of other non-government organizations may be deployed to monitor plants. Another sensor network may be deployed by other non-government organizations to monitor weather conditions: temperature, barometric, pressure, and humidity in the surrounding forest. A government may also deploy a sensor network for other purposes such as natural disasters prevention, forest fire detection, or for military surveillance in the forest. In such scenario, the network performance can be improved by mutual cooperation, instead of applying only a single authority's packet forwarding policy.

Nonetheless, the networks may be unwilling to share their resources with each other because of many reasons that have been driven them. The reasons that determine their cooperative willingness could be grouped as internal or external factors. Internally the individual node has onboard energy. The density of nodes, the location of the BS, deployment area of networks and their topological arrangements are some of the external factors that determine the degree of cooperation. As a result, the intermediate nodes behave non-cooperative by not forwarding the packets to one another. Thus, the performance of such WSNs and their service duration will be limited. Their communication resources in general, and that of their transmission energy, in particular, will be well-maintained, however, when they collaborate. If the networks are willing to do in forwarding one another packets, they are able to reduce their energy consumption.

In this aspect, nodes might be reluctant to work together in spite of they are deployed in a common location. These nodes are not ready to volunteer themselves for clustering, and they could not accept the heavy communication; sometimes they may not participate in the CH selection; if so these nodes do not forward other node's packets. They are interested to adopt behaviors such as a free rider in the clustering scheme. Hence, the approach of grouping such nodes into different clusters, and selecting one node as a leader faces a serious of challenges [63], [60], [99], [64], [65], [66], [67], [68], [70], [71].

On the other hand, even if a non-cooperative node takes the role of CH, it only transmits its packet while dropping the dropping packets belong to other nodes. The other nodes have to retransmit the lost packets once again. Hence, when more nodes exhibit such misbehaviors, the communicational and computational overhead will be increased. These will cost the sensor

networks lifetime, as the energy power of several nodes is depleted early. Thus, the malfunctioning of some nodes limits the QoS that the sensor network provides [23], [24], [25], [26]. The power failures of nodes can cause topology changes or miscommunication or miscalculation in constructing the routing paths. Thus, routing protocols should be aware of and prepare to handle these possible glitches.

Therefore, the cooperation between these nodes should reasonably be managed to boost the quality of network functionalities. This is also based on negotiations to prevent the nodes of one user from being depleted of power while the other networks remain relatively intact, and their nodes with ample battery power. Recently, such nodes' behaviors have been considered for clustering schemes design. In a context of handling the issues that are related to uncooperative nodes, GTs have been utilized [53], [100], [101], [102]. It studies the interdependence and uncertainty of nodes' strategies in a clustering design [93]. Individual nodes analyze their strategies correspondingly the received payoffs in order to adjust their next time strategies. An equilibrium strategy has been reached as individual expected to adopt it.

Considering such modeling schemes, numerous cluster-based algorithms were developed, and these will be discussed in Section 3.4. The issues about communication energy of multiple nodes are also computed in [103]. The computational intelligence is imported into the algorithm to make a wise decision on CHs and member selections. It is aimed to design an intelligent cooperative cluster-based algorithm for WSNs. Thus, it brings the nodes to form a cooperative transmission. The process of CH selection is constructed hop-by-hop in this algorithm. The selection process on the path may take into consideration the position and energy capacity of every node. Besides, the rate of analyzing values [52], and reputation and trust framework [104], [105], [106] were the patterns used to capture the misbehaving nodes for the designing of the cluster-based algorithm.

According to their methodology, these clustering schemes can be grouped into distributed [14], [15], [16], [60], [64], [65], [66], [99], and centralized [67], [68], [70], [71]. When uncooperative nodes autonomously make the decisions of clustering without any central control, the method is said to be distributed. On the other hand, the clustering method is said to be centralized when the information about each node is centrally managed so that the task of cluster formation is performed by a BS. In line with these methods, nodes would be limited to

enjoy some of their features: self-organization and self-configuration. In this context, the performance of centralized clustering scheme is less effective compared to the distributed one.

2.2.2 Radio Energy Model

An energy source is the key to support sensor node's functionalities (such as data collection, processing, and transmission). In due process, the activity of a battery-operated node is terminated when this device has run out of energy: it is considered to be a "dead node," and stops providing any kind of services that the user needs. Replacing batteries may be difficult or impossible in various scenarios of nodes applications. Thus, energy conservation as well as managing are the most important parameters in the sensor networks design [94], [107], [108].

LEACH algorithm that was introduced by Heizelman in Massachusetts Institute of Technology (MIT) in 2000 is an energy-efficient communication protocol [5]. In this algorithm, nodes are assumed to be self-organizing and re-clustering themselves. Figure 2.3 shows the radio-energy model that has been designed for tiny nodes [5], [6], [8]. The designing principle of this model has been considered in line with the standards of configuring communication antennas. Until today this model is widely applicable in various sensor hardware designs [8], [96], [107]. As a result, LEACH is positioned as one of the most widely customized standards for energy-efficient protocols.

Optimizing energy utilization is the main research stream with respect to the battery-operated nodes' internal communications [96], [109]. The energy consumption in the cluster-based algorithm is in accordance with the responsibilities they are assigned to such as being a member or CH. An available energy would further be expended: due to collision, idle listening, overhearing and protocol overhead at Media Access Control (MAC) protocol. In order to reduce the energy consumption during these allocations, a hybrid MAC protocol is proposed in [109]. It uses energy-efficient Time Division Multiple Access (TDMA) for intra-cluster communication and FDMA (Frequency Division Multiple Access) for inter-cluster communication.

Energy is consumed in transmitting and receiving a packet of k bits over a communication channel. In this regard, the transmitter and receiver electronic circuitry of nodes would spend considerable amount energies. In fact, such energy consumption might be regarded to vary in

both electronic circuitries. Initially, the transmitter's electronic circuitry spends energy for the purpose of processing the packets of the node; let it be represented as E_{elec} .

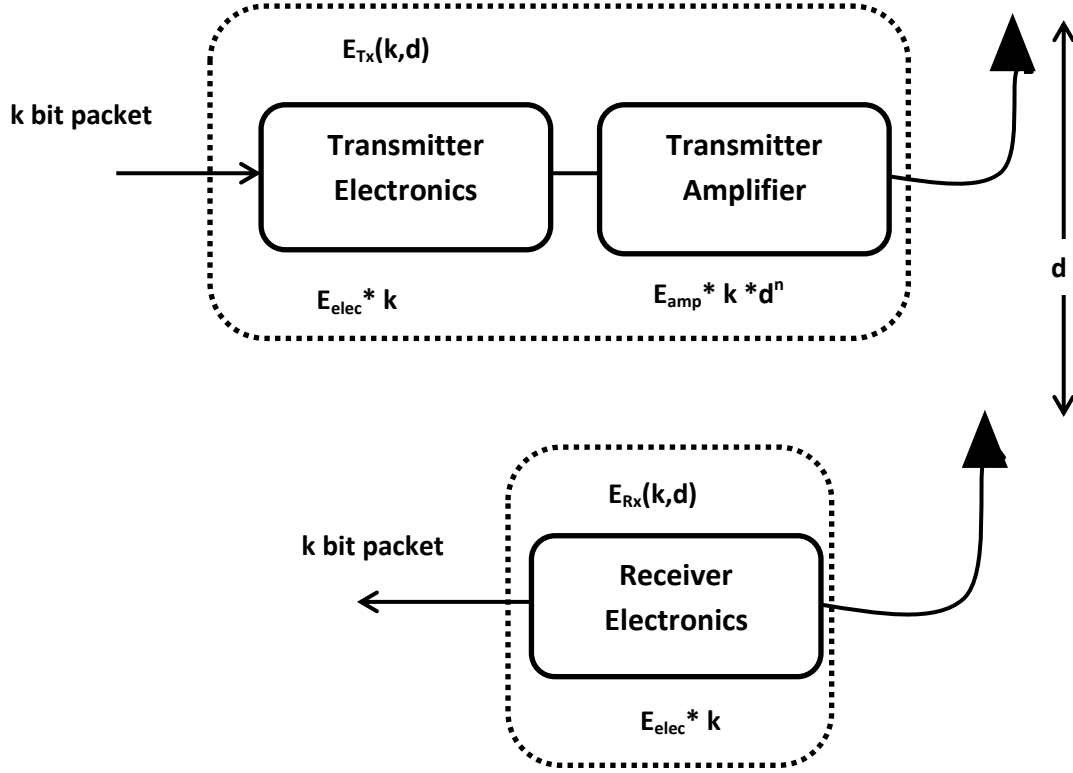


Figure 2.3: Sensor Node's Radio Energy Dissipation Model

Then, the transmitter's amplifier consumes a certain amount of energy for the purpose of achieving the required signal level at the receiver side that must decode the signal correctly and represented as E_{amp} . Therefore, if we represent the distance between the transmitter and the receiver by d , the energy parameter of E_{amp} has usually two variations: the first one corresponds to the square law of distance attenuation (E_{fs}), free space (d^2 power loss); and the second one is related to the proportion of the fourth power of distance attenuation (E_{mp}), multi-path fading (d^4 power loss) channel models.

On the other hand, the receiver also consumes energy when receiving a data packet of k bits; it can be represented as E_{Rx} . Thus, Table 2.1 shows the typical operations and values of radio energy expenditure parameters [5], [6], [8], [97], [98], [107].

Table 2.1: Typical Operations and Values of Radio Energy Expenditure Parameters

Transmitter Electronics (E_{elec_Tx})	50 nJ/bit
Receiver Electronics (E_{elec_Rx})	
$E_{elec_Tx} = E_{elec_Rx} = E_{elec}$	
Transmitter Amplifier (E_{amp})	100 pJ/bit/m ²
Transmit Amplifier types: Free Space Energy (E_{fs})	10 pJ/bit/m ²
Transmit Amplifier types: Multi-Path Fading Energy (E_{mp})	0.0013 pJ/bit/m ⁴
Data Aggregation Energy (E_{DA})	5 nJ/bit/message

The energy dissipated by each node to transmit a data packet of k bits, E_{Tx} , can be represented as:

$$E_{Tx}(k, d) = \begin{cases} kE_{elec} + kE_{fs}d^2, & d \leq d_0 \\ kE_{elec} + kE_{mp}d^4, & d > d_0 \end{cases} \quad (2.1)$$

where the first expression presents the energy consumed by radio amplifier for free space channel (E_{fs}) in transmitting k bit in the shortest distance while the second presents the energy consumed by radio amplifier in multi-path fading channel allocation (E_{mp}) to transmit k bits in a far distance, and d_0 is a threshold.

By equating the above two expressions, the threshold d_0 can be estimated as:

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \quad (2.2)$$

To receive a k bits data packet, a sensor node consumes E_{Rx} amount of energy.

$$E_{Rx}(k) = kE_{elec} \quad (2.3)$$

2.2.3 Network Lifetime

The lifetime of a WSN is accustomed by the consumed energies of the individual node. Energy utilization is one of the main concerns for every sensor network's algorithm designing. Individuals can consume their energy sources in several aspects. These might be during gathering the information in the environment as well as processing and communicating to the

home destination. In these cases, consumed energy would be considered as either “useful” or “wasteful” [13], [107], [109]. The “useful” energy consumption is when individuals utilize their energy for the purpose of sending or receiving data, processing requests and forwarding queries or data to their neighboring nodes. Whereas “wasteful” energy consumption can be due to idle listening to the media retransmitting lost data, overhearing, rejecting neighbor requests or data, and generating or handling control packets. In such contexts, nodes seriously spent their communication energies as collocated networks belong to different owners [110], [111].

However, by efficiently forwarding the packets of one another, they conserve their energies [17], [18], [19], [20], [21], [22]. Thus, each stakeholder maximizes their network performance in terms of coverage and lifetime in providing better services [27], [112], [113], [114]. Accordingly, several methods have been designed for the networks in order to guarantee their cooperation. A cooperative strategy is studied based on a linear programming framework to prolong network lifetime with multi-domain [27]. The different domain of networks in sparse network deployment and harsh propagation environment are considered. In order to capture the essence of multiple-network operations, a framework is theoretically developed and assessed.

A distributed algorithm called HBDR is developed by balancing an energy depletion among heterogeneous sensor nodes [112]. Stackelberg model of game theoretical approach is utilized to study the role of each node. The node plays either cooperative or selfish behaviors. In this regard, nodes playing the parents role are the leaders with cooperative one while nodes playing the child roles are the parents’ followers that are selfishly behaving. The parents make the decision before their followers through predicting what kind of decision will be taken by their children. In such a way, the behavior of children is influenced by their parents. These may help the global benefit of the networks. A balanced tree for the entire network is also constructed using the local information of utility functions. The result has shown that balanced tree based algorithm improved the network lifetime.

Exploiting the diversity of cooperation in the WSNs is provided in order to improve their lifetime [113]. Cooperative transmission and relay deployment nodes are studied using bit-error-rate and power constraints. Cooperative transmission of nodes would be developed to determine which sensors should cooperate and how much power must be allocated to them. This is in accordance with the framework of the decode-and-forward protocol when the

provided algorithm finds the relay locations. When the number of relays and their locations is given, the greedy sub-optimal algorithm is used to obtain the extended network lifetime.

An energy-aware game theoretic data routing algorithm that induces collaborative operation into WSNs is introduced [114]. This is with an assumption of making nodes aware of their interdependence with each other based on nodes centric information. In this manner, they avoid compromised nodes deployment from information gathering. In a pseudo-random way, the payoff function is utilized by every node. In the course of packet transmission, nodes are forced to rotate the selection of their next hop. In this method, the next hop node selection helps each node to extend the network functional lifetime. The linear-regression is also incorporated to evaluate nodes' strategies and amend the strategy space accordingly. In this consideration, the network provides some compensation for failing nodes as a result of adopting inefficient strategies. Yet, the method has its own limitation to deal with misbehaving nodes.

Using a randomized cooperation, the problem of selecting packet relay nodes has been investigated [115]. This has been proposed by considering a game theoretical approach. It uses a Distributed Randomized-Orthogonal Space-Time Coding (DR-OSTC) scheme. Two cases of relay nodes' behaviors are considered: when all nodes are selfish, and when all nodes are prone to cooperation. In the first case, it is considered as an ad hoc network that is consisting of peer nodes where each user owns its nodes in order to carry out only its own data communications. In this assumption, the node of one user wastes its resources if it tries to adopt any cooperation with others. The second case, it is quite in the opposite that it suites into nodes where all of them are belong to the same central network. And this is in line with the objective of improving the performance of each node in the network.

2.3 Overview of GT Approaches

GT has been widely applied in the economic world where autonomous decision makers interact with each other [28], [29], [30]. In the broadest sense, it is defined as a collection of mathematical tools that are formulated to study the situations among selfishly acting individuals in resource sharing. It is the best modeling we have so far in order to study and analyze individuals' behaviors in nature. In this aspect, its concern is toward looking at the best actions for individual players in the situations of different decision making who recognize stable outcomes. Thus, GT has been attributed as a method of modeling and analyzing the

strategic interactions individual decision makers whose actions are mutual, or probably conflicting.

Although GT had started much earlier in designing different scientific research theories, the 1944 seminal book of von Neumann and Morgenstern [116], has been set usually as the birth of GT. The first comprehensive concept about the theory of games and the discourse of economic behavior was formulated in this book. Further, in 1950 invention of Nash Equilibrium (NE) also called strategic equilibrium by Nash [117], is another important milestone in the development of GT direction. In a game of finite players, NE is a profile of strategies so that no player has a unilateral motivation to deviate from it by choosing another strategy. To put it in another way, NE is the form of strategic profile that is the “best responses” to each player in the game. Besides, under a general assumption, Nash also gave a proof of NE’s existence that must be either a pure strategy NE or a mixed NE. The main concept of non-cooperative GT has been a focal point of these strategies analysis. Later in 1994, GT maintained its special attention with the awarding of the Noble Prize in economics to John Nash, Reinhardt Selton, and John Harsanyi.

GT provides a framework and analytical approach for predicting the results of complex and dynamic interactions between rational decision makers or players) [29]. Hence, the players in the decision making can either cooperate or not while striving to maximize their outcomes. In the cooperative game, they are allowed to communicate by an unspecified mechanism in order to allocate resources before making any decision. This is concerned with coalitions which are composed of a group of players for coordinating actions and feasible allocations. However, the individually rational players in the non-cooperative game have distinct interests that interact according to predefined mechanisms. In this case, they cannot reach an agreement (or need to negotiate for cooperation).

In general, GT consists of a set of players, i.e., the participant of the game, a set of strategies for each player and a set of corresponding utility functions [29], [30], [32], [33]. Accordingly, it can be defined as, $G = \{N, S, U\}$. Where N is the players of the game, they are a finite set of participants in the game, denoted by $N = \{n_1, n_2, n_3, \dots, n_n\}$. Each player N has the corresponding action or strategy space, $S = \{S_1, S_2, S_3, \dots, S_n\}$. $U = \{u_1, u_2, u_3, \dots, u_n\}$ represents the set of corresponding utilities or payoffs that the players received in the game.

A. Classical GTs

The core of ordinary GT, Classical GT (CGT), is based on the rationality assumption of an individual player that makes a decision [28], [29], [30]. The player must rationally act to engage in the interaction with other players and has to decide based on the available options or strategies. Maximizing payoff to a player depends on the strategies of the co-players. In CGT the player is considered as a rationally ‘thinking’. This means players determine what is best for them while being aware that the others are also doing the same.

Through these determinations, it is assumed that the players develop a common knowledge in the game. In [29], it is stated that “The common knowledge of a player implies that beyond the fact that all players are rational, they all know that all players are rational and that all players know that all players know that all are rational, etc. and infinitum.” Nevertheless, CGT has no unique prescription about what players should do, i.e., there is no a clear way out for a player. To that end, CGT can only provide intuitions, suggestions and partial prescriptions.

In this regard, without a doubt, CGT has made many successful contributions in solving real-world problems. Yet, regardless of those success cases, its paradigm has been confronted with some limitations that prompt to relax the important assumptions, so as to apply in more realistic cases [29]. Thus, EGT which will be discussed in the next section address the assumption about player rationality.

B. EGT Concepts

An evolutionary biologist like Maynard Smith and his co-workers have introduced EGT into the biological sciences [32], [33]. The aim of their work was to study and predict the outcomes of certain animal behaviors as well as biological evolution. EGT has also been introduced into the field of social sciences to study and understand social learning as well as “cultural revolutions” (i.e., a view of referring the changes in human beliefs, values, social norms, and behavioral patterns) [34]. Likewise, it has found many applications in other fields of studies such as Economics, Sociology, Learning Theory, Physics, Mathematics and Computer Science [29], [34]. The defining feature of EGT is the concept of bounded rationality of the players [31], [50], [118], [119]. For instance, in the biological sciences, the individual in an animal population do not make conscious decisions about the strategy they play. EGT treats the

frequency distribution of the population as the strategy to which some payoff matrices are assigned.

For the first time, in 1973, Maynard Smith and Price formulated and defined an ESS in the framework of symmetric population games [33]. This concept has been introduced to investigate the effect of individual behavior in a large population. If everyone in the population follows this ESS, no mutant can invade it to obtain a better benefit [31], [118], [119]. In simple terms, a population that reached ESS cannot be invaded anymore by a rare mutant. The concept of ESS is actually a ‘static’ perspective because it does not provide any orientation for the dynamics of the definite game. In the evolutionary game, the only thing the ESS anticipates is that the population, which performs a better strategy, has a higher replication or growth rate. Hence, an individual adopting ESS has a higher reproductive success in the overall population than the individuals adopting other tactics.

On the other hand, despite the fact that ESS has more robustness than NE, still it has some limitations. Considering the population evolution, there is no clear answer provided on how the ESS will be achieved, or which of the ESSs are selected and when. Particularly, when the game has more than one ESS such as classic coordination game, the ESS has its own weakness in providing the outcomes. In fact, both NE and ESS has a static condition. Thus, under these concepts, studying the state of the population in the dynamics system is impossible. The limitation of static problem analysis for a very large population is considered and modeled by using the replicator dynamics. Hence, the replicator dynamics has been considered as a solution to overcome the existing limitations of ESS in modeling how the state of a population is evolving. Thus, it has been widely accepted to study the population dynamics: over a period of time in what way the state of the population is changed.

The replicator dynamics was first introduced by Taylor and Jonker [51]. It is the most extensively considered tool to model the system of an evolution. In that context, it provides a dynamic way of describing the evolution of large populations towards NEs (also called stability states): those NEs are stationary points of such dynamics and some of them might be asymptotically stable while others are unstable [29], [50], [118], [119]. In this dynamics, the player in the evolutionary game is represented by a replicator which is also considered as a central actor, while the obtained payoff is usually represented as a fitness. Normally, the

replicator is considered as an entity that has the capability of adopting certain strategies based on the benefit obtained. In the given environmental setting, a set of replicators that were structured in the pattern of interactions among differently programmed agents is said to be a replicator system. Hence, the replicator system is a process of dynamics in which the frequency distributions of those replicators in the evolutionary game keeps changing over time.

2.4 Evolutionary Population Games

The behavior of an infinitely well-mixed population is studied using evolutionary dynamics. Hence, an individual interacts with others in the area with an equal probability of interaction. In their course of interactions, individuals in the total population adopt the possible strategy. Let us assume the strategy to be played is either *Cooperate (C)* or *Defect (D)*. Accordingly, the total population should be fractioned into x_C C's and x_D D's. From these fractioned populations, a group of N individuals is randomly sampled.

In this scenario, the group of the population sampling consists of j C's and $N - j$ D's. This population sampling is awarded a payoff of either $P_C(j)$ or $P_D(j)$ depending on their possible strategies, where $P_C(j)$ and $P_D(j)$ are the given payoff for the population of those adopting C-strategy and D-strategy respectively. Thus, the strategy fitness is computed by averaging the payoffs over all the possible group compositions. Let us assume that the fitness will be π_C (the fitness of C's strategies population) and π_D (the fitness of D's strategies population) that were computed in [120], [121].

With this regard, the evolution dictates that a strategy of the population that performs better than an average will spread in the whole population at the expense of the other strategy. In this case, the population prefers to follow a certain strategy to get a better payoff. As such, the population should be grouped according to their C-strategies and D-strategies. Accordingly, by introducing a replicator dynamics, the portion of such grouped population should be estimated [50], [51], [118], [119].

Hence, the portion of C-strategy population should be:

$$x_C' = x_C (\pi_C - \pi_{avg}) \quad (2.4)$$

where π_{avg} denotes the average fitness of the population, $\pi_{avg} = x_C \pi_C + x_D \pi_D$.

Similarly,

$$x_D' = x_D (\pi_D - \pi_{avg}) \quad (2.5)$$

Equations 2.4 and 2.5 could be simplified by omitting the dependence of the population fitness on x_C and x_D . This will be analyzed in evolutionary dynamics since $x_D + x_C = 1$, then, $x_C = 1 - x_D$. Accordingly, with a simple computing of the above equations, a single differential equation will be formed, where $x \equiv x_C$.

$$x' = x(1 - x)(\pi_C(x) - \pi_D(x)) \quad (2.6)$$

It is an equation of standard replicator dynamics which can be used in order to track the evolution of C's in an infinite well-mixed population (i.e., the encounters between the players are completely random).

2.4.1 Social Dilemma Games

The evolutionary game is becoming an important tool to study cooperative behavior in the social dilemmas with the competitive setting. Such games will be studied as of 2-Person and N-Person Public Goods Games.

A. Symmetric 2-Person Games

In simplest cases, the game has two individual participants [29], [30]. These individuals interact with each other to receive a certain payoff. In one-shot player's interaction, the possible payoff that the players get would depend on the strategies they have chosen. Table 2.2 summarizes the payoff for the most popular symmetric 2x2 games [29], [30].

Table 2.2: The Possible Payoff Notation of Symmetric Game

Player A\Player B	Cooperate (C)	Defect (D)
Cooperate (C)	(R, R)	(T, S)
Defect (D)	(S, T)	(P, P)

Where, the standard shorthand notation should be defined as, R – “Reward for mutual cooperation,” T – “Temptation to defect,” S – “Sucker's payoff,” and P – “Punishment for mutual defection.”

The payoff representation that player A and B collect during their interaction: both players obtain the reward R when they cooperate; otherwise, they obtain punishment P if both of them prefer to defect; when player A with strategy C meets B that has strategy D, A obtains the sucker's payoff S , whereas player B gains temptation to defect T and vice-versa.

Usually, this type of game is said to be symmetric game since the players obtain the same payoff when executing the same strategy. This means every player gets an equal payoff, regardless of the player type (i.e., whether A or B). Whereas, in the non-symmetric (also known as asymmetric), each player receives a different payoff.

- i. **Prisoner's Dilemma (PD):** Probably it is the best well-known example that illustrates the problem of cooperation in which two players simultaneously choose one of the two possible strategies; to cooperate C or to defect D [28], [30], [122]. Accordingly, PD shows the analysis of why two players might not play C, even when it is in their best interests. In one-shot of PD, defection is the better action in a well-mixed or fully connected population, regardless of what opponent decided. As such, according to Table 2.2 representation, the payoff will be ranked in the order of $(S < P < R < T)$. The additional constraint of $T + S < 2R$ is considered in the case of repeated version (Iterated Prisoner's Dilemma).
- ii. **Snowdrift Game (SG):** was introduced initially to describe the system of action when two drivers are jammed on the road by a snowstorm [120], [121], [123]. To go home, first the road must be cleared. The drivers have two options: (1) to get out and start shoveling (cooperate); (2) to remain in the car (defect).

Accordingly, if both drivers are willing to shovel the snow from the road, they share the cost c for doing the shovel and each of them obtains the benefits v of getting their home. In this case, each receives the payoff of mutual cooperation, $R = v - \frac{c}{2}$. Otherwise, if both drivers choose not shoveling the snow, then they obtain zero benefits ($P = 0$), since, they do not get home. If only one of them shovels the road then both of them get home with the different cost of expenditure, i.e., the cooperator gets ($S = v - c$) benefit, whereas, the defector gets the income of ($T = v$) in which its benefit is not reduced by the cost of shoveling.

In one-shot of SD, the payoff that each player received should be arranged into $(T > R > S > P)$. In this game, the player obtained the maximum payoff or benefit by doing the opposite of

what the opponent does. This type of game favored a mixed equilibrium. Indeed, it has two non-symmetric NEs profile: (C, D) and (D, C). In this profile of SG, two different players can coexist in a stable equilibrium.

- iii. **Stag Hunt (SH):** can be illustrated as hunting scenarios, where two hungry hunters go to the woods with the aim of catching a stag or at least a hare than nothing [29], [124]. According to Table 2.2, its payoff is represented by $(R > T > P > S)$. This implies that $(D, D) > (C, D)$ and $(C, C) > (D, C)$. This game has a NE at (D, D) from the NE of PD; in addition, it has Pareto efficient equilibrium at (C, C). The latter case happens due to this game provides the highest payoff for both hunters if they reached an agreement of cooperation.
- iv. **Harmony Game (HG):** is the last game that is also rarely mentioned in the GT analysis [124]. As the name implies it does not represent any social dilemma conflict. Usually, it represents an ideal situation, where the C's steady progress with null effort. Hence, from table 2.2 the payoff rank of HG can be $(R > T > S > P)$. Only a single equilibrium exists in this game that will be at (C, C).

Table 2.3: A Partitioning of the S-T Plane which Displays the 2x2 Games of Symmetric

1	Harmony Game (Cooperate)	Snowdrift Game (Opposite)		
0	Stag Hunt (Same Strategy)	Prisoner Dilemma (Defect)		
-1	0	T	1	2

S-T Plane: In order to provide a fixed scale for the payoff, traditionally, the values of R and P will be imagined as $R = 1$ and $P = 0$. Then, by applying such constraints into 2x2 games, for parameters T and S, their values will be selected. The definition of such games will be enabled by considering their equilibrium stability [29].

B. N-Person Public Goods Games

In reality, there are many different types of problems that cannot only be modeled by the assumptions of two-player interactive games. If the group sizes of the participants increase from two players to many player interactions and in view of these new independent parameters was also added into the game. As such, it has been addressed by generalizing the previous theory into the game of involving more than two-players that simultaneously interact [29],

[124]. Hence, the general representation for analyzing the problem of cooperation in groups of N interacting individuals ($N > 2$), gives a rise to a class of N -person dilemmas, also known as Public Goods Games (PGG). A model of PGG was considered in [124], in order to study a group of N -players interactive problem. As such, each player is assumed to be interacting with the group either through contributing a public good or does nothing.

Usually, finding a set of possible equilibrium is the heart of the GT, regardless of which type of game will be investigated as a solution. In a PGG, the individuals have an option of whether to contribute to a common goal or not, in which a benefit is extracted and shared by everyone in the game. Hence, the strategy of the individual player in the collective action needs to be fully analyzed for a multiplayer game to reach mutual equilibrium.

Moreover, individuals that play together in this type of game will be determined by the size of the participant (eg., when N is the size of participants, they composed of j C's and $N - j$ D's strategy). Commonly, this type of game will be reduced to the previous case of 2-person games when $N = 2$. Given the complexity added into N -Person games, we discuss the following PGG:

i. N-Person Prisoners Dilemma (NPD): considers a situation when each of N participants in the game has a choice between two actions: '*cooperating*' or '*defecting*'. Players are cooperating with each other for a 'common good' or are defecting 'for their own short-term interests.' In such context, the payoff they receive depends on what the player itself chooses as well as what others choose [29], [122], [124].

A more realistic and general game of the N -player Iterated Prisoner's Dilemma game (NIPD) was studied [122]. It aims to model the problem of N -player interactions. The impact number of players (group size) in the NIPD on the evolution of cooperation is experimentally conducted first. And the results show that cooperation is less likely to emerge in a large group when compared with small. Second, the issues on the co-evolutionary learning-generalization ability of evolved strategies from the point of machine learning view have been conducted. And the experiment shows that the importance of environments in which each individual is evaluated, and their effects are there on the generalization ability.

ii. N-Person Stag Hunt Game (NSHG): is a generalization of the 2-person SH game when the group size of the hunters are increased [29], [124]. Similar to SH, the obtained payoff

will be maximum in NSHG if all individuals play the same coordinative strategy. Unlike the other games, in NSHG a C's strategy contributes to the group by paying a c cost and D's strategy does nothing. However, in this game, in order to harvest the benefits, the required number of contributors' has to be reached above some threshold in the group member. As the size of contributor is increasing in the group participation it leads to harvesting better benefit.

iii. N-Person Snowdrift Game (NSG): is studied through incorporating the effects of N-person interaction into two-person games of SG [120], [121], [123]. It is N-person generalization of SG. In the attempt of interactions toward cooperation, NSG revealed that a benefit received by each individual in the group is directly associated with its interactions.

By assuming 'cooperative' and 'defective' strategies, it is possible to present this game. So, a total cost of completing the task should be shared among those players whoever has a willingness of cooperating. Contrarily, a player might play defective strategy hoping that some other players will do the task on behalf of it. From this perspective, as long as the task is completed by cooperators the defectors get a benefit for taking this action. Otherwise, the player gets nothing if the task could not be completed since all N-person players do nothing.

As it has been mentioned in the above NSH, with increasing the number of C's in a group the benefits will be better. There are some situations in this game, however, where this is not the case. For instance, in order to construct a building, the minimum number of workers should be enough, yet the benefit obtained is always fixed. In addition, the less individual effort will be required to construct if more workers are ready to work together, i.e., the more C's are there in a group, the better off are the D's.

Both PG and SG have been widely accepted in modeling many real-world situations of social dilemmas [29], [120], [122], [125], [126]. The strategic evolution in an iterated multi-player social dilemma games is studied by modeling small-world networks [126]. The study considers two games, namely N-player Iterated Prisoner's Dilemma (NIPD) and N-player Iterated Snowdrift game (NISD). The analysis has shown that in both games the regular lattice with strong local neighborhoods is highly favorable toward the cooperative behavior.

In a study of cooperation in social dilemmas, the evolution of human cooperation is examined both under Iterated Snowdrift Game (ISG) and Iterated Prisoner's Dilemma Game (IPG) [125]. The results show that the cooperation of iterations in the ISG consistently leads to higher levels

than in the IPG. These significant differences happen since the cooperation in IPG has higher risks for someone compared to that of ISG. That is the cooperation is highly oppressed in IPG. It is to say that in snowdrift the risk of being oppressed by someone who does not cooperate is lower. In the prisoner's dilemma when the opponent defects, it is a greater risk to cooperate with someone, whereas, in the snowdrift game, even when the opponent cannot do anything, shoveling the snow will be always better for someone to go home. In other words, the higher level of cooperation in the snowdrift is the reason why it is more favored by natural selection (such as human cooperation). Thus, the cooperation model of ISG is more real-life related compared to IPG.

Furthermore, the cooperative phenomenon of PD game was investigated in [29], [125]. This game has many difficulties to rank and evaluate its payoff. As a result, it might bring a serious of uncertainties into a model if one wants to study in practice the emergence of cooperation. Consequently, as an alternative to PD, evolutionary SG has been widely suggested [120], [121], [125]. Evolutionary SG has become greatly appealing in the recent studies of a model for competing settings such as in network communications to design cooperative spectrum sensing [127], [128]. Thus, SG is an appropriate model to adopt if one wants to design an evolutionary system that achieves higher cooperation. As a result, this game is considered as a tool to tackle the problem of non-cooperative setting sensor nodes.

2.4.2 Dynamic Equilibrium Behaviors

In the game of population evolution, the types of equilibrium behavior that can be reached should be gathered under a global and internal equilibrium [120], [121], [124]. The cases of the equilibrium strategies where the population prefers to adopt are always said to be global equilibrium. For instance, the replicator Equation 2.6 has two global equilibriums; when the value of $x = 0$ or $x = 1$. Thus, when the value of $x = 0$ the population should be shifted toward fully D strategy otherwise fully C since the value of $x = 1$.

In addition, the equation $\pi_C(\dot{x}) - \pi_D(\dot{x}) = 0$ has at most $N - 1$ internal equilibrium, when $\dot{x} \in (0,1)$. The sign of x' deduces the nature of this equilibrium at the dynamic population states. Thus, in Figure 2.4 the availability of these simple equilibriums are summarized [124]. The trends of an evolution would be represented on the diagram by the direction of the arrow: it shows whether the fraction of C's strategy population increases or decreases.

The condition of one strategy domination should be either D-dominance or C-dominance. For instance, it has been shown in Figures 2.4a and 2.4b. This should happen in the population, respectively when x' is always either negative or positive. Regardless of the initial population of condition $x(0)$, the selection will always favor the possible strategies. That means the population adopting one strategy will grow up always. After sometime this will lead the state of the population toward adopting either full D, if $x' < 0$ ($x = 0$ stable and $x = 1$ unstable) or full C, if $x' > 0$ ($x = 0$ unstable and $x = 1$ stable). These types of equilibriums have been shown in Figures 2.4a and 2.4b respectively. The former equilibrium is typically a PD or a NPD while the latter represents a HG.

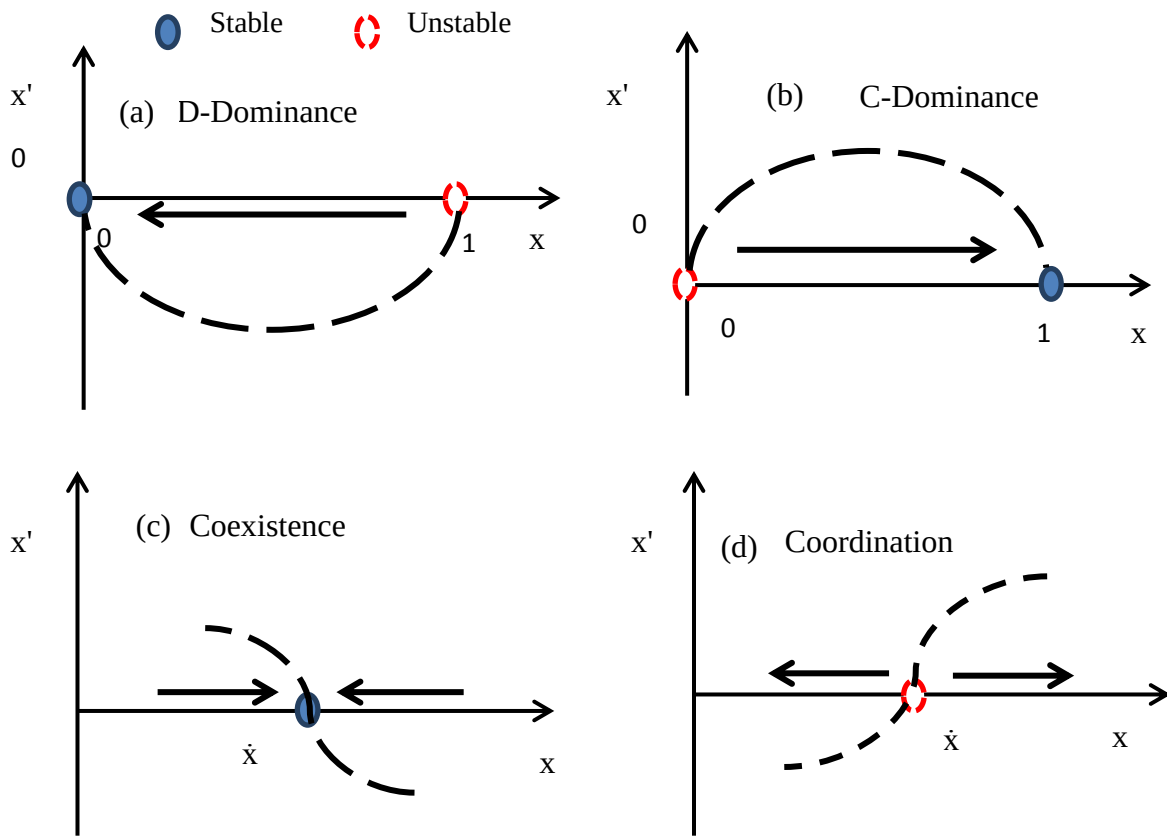


Figure 2.4: Overview of the Possible Dynamic Equilibriums: (a) and (b) Represent Dominance Situations, either by D's or C's respectively; (c) and (d) Specify the Two Types of Internal Equilibrium Points, Coexistence and Coordination respectively

On the other hand, there are two types of internal equilibrium. In the evolutionary game, when they present, the dynamics of the population should arise in more interestingly. Hence, these dynamic equilibriums should be [29], [124]:

- The equilibrium is said to be *stable* when $x' > 0$ for $x < \hat{x}$ and $x' < 0$ for $x > \hat{x}$. As it has been shown in Figure 2.4c, it is called a *coexistence point*: for any $x(0)$ near $\hat{x}$, population selection will make the convergence to the equilibrium in case there is no other equilibrium available in such area. In such condition, there is a different equilibrium strategy that should be allowed to coexist in the population.
- The equilibrium is said to be *unstable*, on the other hand, when $x' < 0$ for $x < \hat{x}$ and $x' > 0$ for $x > \hat{x}$. This has been shown in Figure 2.4d, it is called a *coordination point*: population selection will decrease x , for any $x(0) < \hat{x}$; and the selection will increase x instead, for any $x(0) > \hat{x}$. The evolution strategies are always coordinated by equilibrium. Such a condition is also called *bistability*.

Another type of special equilibrium that was not mentioned in the above discussion is also named *meta-stable equilibrium* (it is also not shown in Figure 2.4). The behavior of this equilibrium is neither stable nor unstable. For instance, in the context of the N-person Snowdrift Game (NSG), it can appear, however only for a particular combination of the parameters. When the strategy of C's and D's, both provide the same fitness, the selections are said to be *neutral*. In order to give an illustration of what this represents, let us look into Equation 2.6 once again. The form of equation $\pi_C(x) - \pi_D(x) = 0$ will represent the fitness difference of the replicator, for all $x \in (0,1)$. Hence, an equilibrium will be any of $x(0)$. For a more detailed study of the meta-stable equilibrium see [29], [124].

2.5 The Role of GTs in Designing WSNs

GT has been widely employed into the theories and systems of networking developments [53], [93], [100], [101], [102], [129]. In light of sensor networking operation, it has been regarded as an important and suitable basis for accomplishing practical and feasible designing aspects. GTs are also important in solving the requirements of WSNs since they are powerful and rich in mathematical abstractions. Thus, being also rich in strategic reasoning, GT deals with the

formulation of non-alien individual nodes. Besides, it is an efficient method for solving the strategic interaction of individuals in optimizing their communication resources.

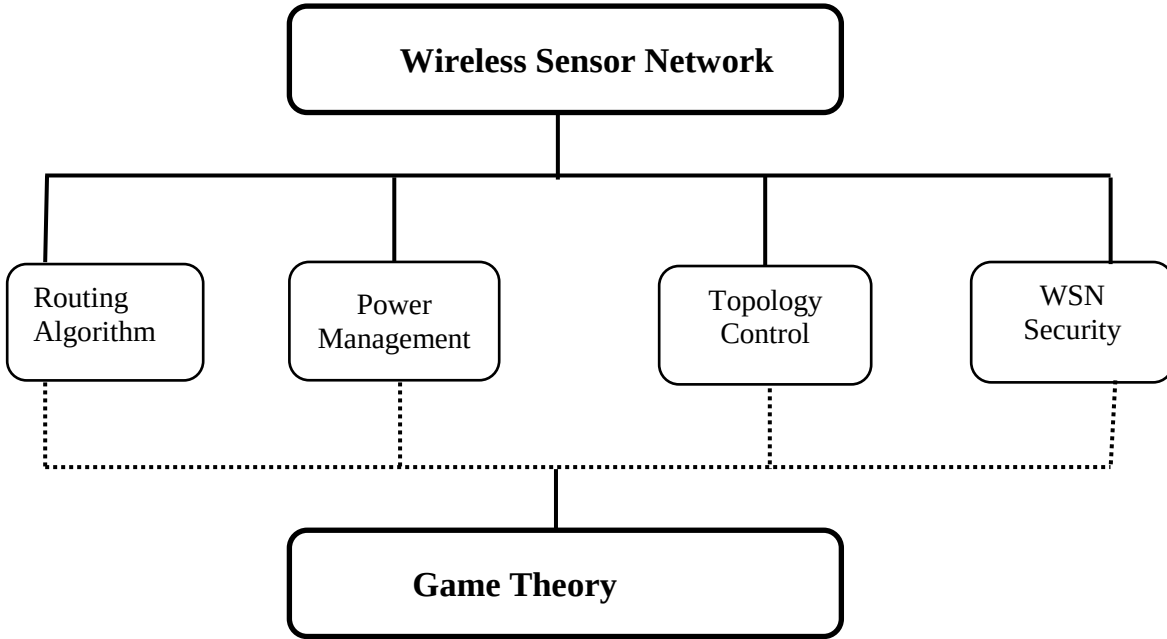


Figure 2.5: The Relationship between WSNs and GTs

In this section, we describe how sensor nodes' interactions can be modeled as a game. The dynamic natures of nodes are able to account for game approaches. Thus, the roles of GTs in designing the WSNs are studied in [53], [93], [100], [101], [102]. Considering the applications of GTs, the relationship between GTs and WSNs designing is summarized in Figure 2.5 which is restructured from [101]. Accordingly, it is grouped into designing of routing algorithm, power management, topology control, and WSNs security. Packet forwarding, bandwidth and spectrum allocation, QoS control and coverage optimization are also some other applications where GT has been applied in WSNs.

2.5.1 GTs for Routing Algorithm

GT has been acceptably incorporated into the current designing of routing algorithms. This will be able to account with respect to catch up and modeling the behavior of nodes. It is also used for harmonizing the communication energy of each node for allocating dynamic and reliable routing path and many others. An optimal packet routing has been designed using an approach of GT for WSNs, in the presence of uncooperative node [130], [131], [132], [133]. A model of GT based reliable routing algorithm has been provided for selfish nodes [130]. The employed

GT finds the balanced equilibrium between the reliability and resource limitation of nodes. The observed NE between these sensor nodes would be assumed. Then, it is incorporated into DSR algorithm that lately named as DSR-G. It is shown that packet forwarding has better performance in DSR-G. This is due to the less impact that the selfish node has on the DSR-G when compared with that of DSR.

Routing packets from the source node to the destination was formulated by an approach of Stackelberg games [131]. Accordingly, the game is played between a pair of source-destination and selfish nodes. Here, the two-stage of Stackelberg game is modeled using the interactive behavior of source and relay sensor nodes. Then, the formulated relay nodes (also called node leaders) are proposed as a solution using the concept of payoff-maximization. The equilibrium strategies are achieved by modeling since the relay nodes enter into cooperation of routing packets. In this way, the provided model balance energy consumptions between nodes.

Routing congestion game was developed for node entities of selfish behaving in WSNs [132]. In this type of network, selfish nodes independently control the path of packet communication. So, each selfish node player participates in the congestion games with an objective of selecting an appropriate packet routing. As a result, everybody selfishly chooses a path from a source node to a destination. In certain circumstances, the achieved equilibrium guides their behaviors in selecting the path having a minimum edge congestion and service cost.

Using GT approach, finding an optimal path for routing packets has also been considered in [133]. The reliable paths, energies, and traffic loads were incorporated into the model of pricing and payment in order to determine such path. If the destination node successfully receives a packet, it has to pay M amount to the source node. Further, the source node has to pay the same Q amount for each packet transmitted by intermediate nodes since they are cooperating. Since the benefit earned by each node for transmitting the packets is more than the cost, any node is willing to do in the game. Accordingly, the nodes allocate themselves in the packet transmission path in order to secure a positive payoff profit. Several cluster-based routing algorithms have been designed (see Section 3.3) by adopting the concepts of theoretic games.

2.5.2 GTs for Power Management

The energy intake of nodes must be judiciously managed for the purpose of extending the duration of sensor networking functionalities. Hence, energy saving and power control strategies are incorporated into communication devices. In this regard, GT plays a leading role with respect to managing energy among nodes. It considers the local knowledge about nodes as an independent player. For this purpose, taking the solution of GT strategies was encouraged in recent years [134], [135], [136], [137].

A non-cooperative GT based power control is considered for virtual multiple input multiple output wireless sensor network (VMIMO-WSN) communication architecture [134]. An incomplete information game was provided in which the individual node does not have complete information about the strategies taken by other nodes. To decide the optimal power level at which a node needs to transmit and maximize its utility, the NE is considered in the architecture of VMIMO-WSN.

Using a non-cooperative versus cooperative game, power control algorithms are proposed for the formation of networking topology of selfish and cooperative nodes [135]. As such, a GT is applied to investigate the conflicts and coalitions between competitive sensor nodes. They interact with each other locally to form the clusters. The marginal contribution of individual node toward coalition is computed by Shapley value in order to provide an incentive for the one cooperates. Thus, through establishing the local coordination, their energy allocation is efficiently shared. To meet the demand of Multi-services WSN, GT is considered for designing a power control algorithm [136]. As such, a model of a non-cooperative game has been applied for the performance improvement of distributed Code Division Multiple Access (CDMA).

Considering the misbehaving nodes, the power control problems are formulated by using strategy versus joint power optimization technique [137]. In the strategic power optimization, nodes are considered as rational agents in the power game that need to adjust their powers strategically to minimize their own energy. On the other hand, in the joint power optimization, the transmission powers of sensor nodes are adjusted to minimize the aggregate energy expenditure. Then, a simple game-theoretic model of two-sensors that play the power game was developed. In this game, the existence of NE has derived analytically. It is assumed that by adopting unilateral and un-detectable strategies, any node cannot follow a different energy

optimization strategy than what other nodes follow. Lastly, to protect the wireless network from energy attacks (for instance energy misbehavior node) effective defensive method has been developed based on the intelligent adversary.

Furthermore, by using GT approaches, in [138], [139], the models of communication energy saving are developed. These models manage the network resources by changing the topologies that would be through adjusting the transmission power of the nodes. In these models, a topology that changes the networks to adjust the transmission power of the nodes has been considered. GT based scheme is also designed in [140], [141] for sensor nodes' power management by adjusting their communication coverage. Additionally, in [112], [131], Stackelberg game approach is assumed with respect to designing the model of routing algorithm that balances the communication energies among those non-cooperative relay nodes.

2.5.3 GTs for Topology Control

Designing an appropriate network connection and routing algorithm is an extremely important issue in order to maintain the balance between packet throughputs, delay, and energy lifetime [1], [2]. In this regard, a method of grouping nodes into clustering topology provides efficient energy communications [72], [81]. Thus, this enhances transmission reliability by reducing message overhead in the course of transmitting packets. In this aspect, GT has played an active role in order to formally model the interconnections and interactions of sensor nodes [82], [138], [139]. Accordingly, it is a suitable tool to analyze the connectivity of the network in the presence of selfish nodes.

A non-cooperative GT is utilized in [142] in order to configure the communication of ad-hoc networks where an individual node is selfish and seeks to maximize its utility. From this perspective, the results of a topology formation are analyzed when nodes interact globally with each other. It applies GT in order to study the convergence behaviors of nodes. Thus, an example of topology control games is presented in line with a distributed best response algorithm. However, recently the weakness of this work is improved by a Quasi Distributed Topology Control (QDTC) algorithm [82]. The latter incorporates the methods of clustering nodes which assumes that the sensor plays the game with their neighbors that they achieve fairness and fast convergence rate.

A game theoretic approach also called Cooperative Topology Control with Adaptation (CTCA), is applied in designing network topology [138]. The solution is proposed by mapping the problem of maximizing the network's lifetime into an ordinal potential game. At this juncture, each node plays the ordinal potential game through adaptively adjusting their transmission power to extend their life. In CTCA, an employed GT allows the cooperation between nodes by forming the arrangement of network nodes. Moreover, a non-cooperative GT was applied to control the topology and joint power of sensor nodes [139]. In this game, as the algorithm is distributed, nodes exchange information only with their neighbors to formulate and adjust their own transmission power.

2.5.4 GTs for WSN Security

Ensuring the security of WSNs is critical and important in order to widely utilize their applications. In this regard, GT provides a mathematical notion that is supposed to analyze the strategy of non-alien individuals in the networked natures. As such, the scenarios where multiple players with contradictory objectives compete with each other in the sensor networking communication have been considered. Regarding the GT approaches, several frameworks have been designed for WSN security [55], [56], [57], [58], [59].

Such security problems should generally be grouped into preventing Denial of Services (DoS) attacks, intrusion detection, strengthening security, and coexistence with malicious nodes according to the taxonomy of WSNs security [53], [101]. The security problems of preventing DoS attacks and strengthening the security of WSN applications have been investigated by using cooperative game [55] and repeated game [56]. In addition, while the non-cooperative game has been proposed for intrusion detection [57], the signaling game has been formulated to develop the notion of coexistence between malicious and regular nodes [58].

Further, GT has been applied in the designing of an effective communication coverage of sensor nodes [140], [141]. GT based mathematical framework is considered to maintain nodes coverage [140]. In this work, by natural mapping of the communication layer of each node, a distributed scheme is developed. This scheme measured the topology control systems in identifying suboptimal. With the help of decision-making or control authority, the status of node player is attributed to efficient systems components. In this context, the convergence into NEs is characterized as the performance of systems in terms of coverage to enhance energy

utilization. GT has been used by an objective of improving the coverage of self-optimizing nodes [141]. In this regard, an energy-aware algorithm has been adopted by using gur-game. This algorithm attempts to either activate or deactivate each node in order to achieve the maximum region coverage in conserving energies.

Furthermore, by considering the strategy that misbehaving nodes adopt, mutual packet forwarding operation have been ensured in [18], [19], [21], [143]. GT approaches which analyze the forwarding strategies are considered in such designing. In addition to what has been discussed so far, there are other areas where classical GT has been applied, controlling QoS [132], bandwidth allocation [35], [36], and managing the communication resources of sensor networks [144] are some of them.

2.6 Summary

Several nodes might be deployed in order to assist mankind in various areas. Often sensor networks are designed for specific application and they are deployed for special purposes in order to solve user intended applications. After their deployments, nodes are expected to transmit the data sensed in their physical phenomena. In this respect, the designed routing algorithms of WSNs have many shortcomings. Because of these nodes are battery-operated energy conservation is one of the most important aspects in algorithm design. In this regard, in order to extend the network lifetime, the responsiveness of cluster-based routing algorithm has received much attention when compared with other routings.

GT approaches have been considered with the objective of modeling the behaviors of misbehaving nodes: self-organizing, self-configuring, and self-optimizing of individual nodes should be characterized. Several models have been developed in order to minimize the effects of selfish nodes. In this consideration, studying evolutionary game has got much popularity to design wireless networks [59], [145], [146], [147]. The developed model studies the populations of large-scale nodes. The strategic nature of evolution is adopted into the condition of behaving nodes. An EGT approach is also used to develop an adaptive selection of cryptographic protocols [59]. The nodes dynamically participate in the evolutionary game to select the defensive strategy that helps them to behave in accordance. In such manners, they reach an evolutionarily stable. The more generic results illustrate that nodes quickly return to ESS even after perturbation.

An evolutionary game approach to design congestion control protocols in wireless networks communication (for instance sensor nodes) is introduced for non-cooperative networks [145]. The convergence of the replicator dynamics has been studied and achieved. It considers the problem of individually non-cooperative nodes into the Hawk and Dove game. The contradictions between maximizing the secrecy rate of a node and minimizing power consumption for data transmission is solved [146]. A non-cooperative evolutionary game is adapted into clustered WSNs. An approach to compute the secrecy rate between a node and the responsible CH is constructed by developing the classical wire-tap channel. A biologically-inspired framework for improving the performance of fault-tolerant WSN is created using an evolutionary game approach [147]. In order to collect the information in a sensor network a collection protocol called Evolutionary Collection Protocol (ECP) is developed. The ECP sends the collected information towards the destination node in the sensor network. An evolutionary game is also analyzed in designing routing algorithms. In this aspect, it has been considered to model the behavior of an individual node in the cluster-based algorithms of [148], [149].

In general, there are several schemes that were developed by using evolutionary games. With respect to this, the typical existing examples of EGT based schemes are the following: MWSNs enforcing cooperation by punishment [20], developing cooperation in underwater sensor networks [22], promoting the selfish nodes to cooperate with each other [150], design cluster-based algorithm for selfish sensor nodes [149], [148], adjusting multiple-access control and power control [151], learning for an optimal strategy [152], collaborative spectrum sensing [127], distributed spectrum sensing for cognitive radio networks [153], cooperative spectrum sensing based behavior dynamics [128], joint spectrum sensing and access for cognitive radio networks [154], whether and when to share collaborative spectrum sensing [155].

CHAPTER THREE: RELATED WORK

The important related works around our research challenges are reviewed in this chapter. Methods of mitigating selfishly behaving nodes, multi-class networks cooperative methods, and cluster-based routing algorithms that mitigate with such nodes are discussed in details. GT approaches are particularly considered.

The chapter is organized as follows: Section 3.1 discusses the works to mitigate the behaviors of selfish nodes, contributions, and their limitations. The research related challenge of cooperative packet forwarding in MWSNs is discussed in Section 3.2. In Section 3.3 the details of the current state of the art that focusing on GT approach to mitigate with misbehaving nodes on the designing of cluster-based algorithms is assessed; the contributions and their limitations are also summarized. In Section 3.4 the summary of the chapter is presented.

3.1 Methods to Mitigate the Selfish Nodes

Various methods have been proposed to mitigate the misbehaving nodes. Some of these are GT-based, selfish node identification and isolation, trust and reputation, and credit-payment mechanisms.

A) GT-based Mechanism

In [35] the contention window allocation problem that occurs as a result of selfish nodes has been solved using GT-based approach. It is utilized by assuming each node as a player, the throughput as a payoff, and the size of the contention window as a move. In this mechanism, a simple, localized and distributed protocol of Pareto-optimal NE is developed to guide multiple selfish nodes to reach cooperation. Detection and punishment technique is also incorporated into those nodes that exhibit a non-cooperative behavior. Lastly, simulation analysis for rational cheating has been conducted on IEEE 802.11 of CSMA/CA networks to obtain better network throughput.

The Contention Window Select Game has been defined based on a GT [36]. A node selects its own contention window to control the probability to access. But, the uniqueness existence of NE is considered in this contention game. The mechanism of penalizing the nodes that decrease their contention window without any permission was proposed according to repeated GT.

However, the proposed approach assumed that nodes are rational in order to prevent selfish users from the network.

COMMIT protocol is developed in [77]. It intends to establish a route for packets communication between source and destination nodes that selfishly behaving. VCG payment scheme in combination with a game-theoretic technique is used to achieve the truthfulness of sender nodes. In a distributed manner, every individual node rationally acts to discover the most energy-efficient routing between two nodes (source and destination). A NE is analyzed to stimulate the cooperation between nodes by developing a truthful protocol. In NE notion, a node has no incentive for changing the strategy, assuming that the other nodes do not change their strategies as well. Regardless of the strategy played by other nodes, behaving truthfulness is always better for everyone. However, it is identified that due to weak NE achievement, the network performances have still been exploited by misbehaving nodes.

A GT is also introduced to analyze the existing internal incentive mechanisms based on punishment through channel jamming [37]. It has been stated that jamming yields a fair NE for all nodes. Thus, all nodes can provide incentives to their neighbors by forwarding packets. It has been said that even when there is a neighbor node acting in a collusive manner by communicating only with one another, jamming is possible to enforce a selfishness. Nevertheless, the price of jamming can be sometimes high as it consumes extra energy (i.e., punishment can be unaffordable for resource-limited nodes). For more GT-based approaches, see under Sections 2.5, 3.2 and 3.3.

B) Selfish Node Identification and Isolation Mechanism

An approach to identifying and removing greedy nodes in WSNs is developed in [38]. This approach is called Energy Efficient removing Greedy Node (EEGN) algorithm and it aims to study the problem of greedy nodes that occur in the multi-path routing. The concept is based on the number of packets that the node can directly send and receive from its neighbor. In this method, the number of packets sent out is compared with the number of packets received for the same nodes. So, if a node under investigation considers the same packets, this shows that the node is not greedy. Otherwise, this node was used to send out different number packets, i.e., it may not send all the packets to the destination. In this case, this intermediate node must be

identified as a greedy node and should be removed from the communication path. EEGN is only provided theoretically, and its applicability is not supported by any kind of simulation.

The techniques designed in [39], [40] are also used to identify and isolate misbehaving nodes. Nodes that fail to forward would be identified and isolated as misbehaving nodes. In [39], related mechanisms called “watchdog” and “pathrater” approaches are first introduced, respectively to identify misbehaving nodes and to keep the state of nodes. Then, to regulate the behavior of each node, they must be always running. By using “watchdog” approach, a node that forwards a packet verifies whether the next hop node also does the same. If such node does not forward, a failure tally is incremented. Thus, for each node, the tally is checked if it exceeds a certain threshold value whereby the node is recognized as a misbehaving. In the course of path selection, the “pathrater” approach utilizes the current information about misbehaving nodes to avoid them from the selected path.

To overcome the shortcomings in the traditional “watchdog” mechanism [39], the work is extended into [40]. As such, every node needs to monitor the behaviors of its neighbors’ instead of only monitoring its next hop behavior. Behavior evaluation mechanism of direct last-hop neighboring nodes is used to collect information from MAC layer when the control packets RTS/CTS/DATA/ACK are enabled. However, this approach has still limitations in many aspects. To begin with, identifying several kinds of misbehaving nodes (mostly distinguishing misbehavers from transmission failures and another kind of failures) are very tough. Again identifying these nodes in the case of collisions or weak signals overhearing does not always work. Integrity and authentication are also not guaranteed for the messages routed between different nodes. Executing these mechanisms is also unattainable for tiny sensor nodes.

In [41], detecting and excluding the selfish nodes from WSNs is developed. A selfish node detecting algorithm that considers partial greediness and replication of allocation techniques are considered. In the proposed algorithm, first, each node detects the greedy node according to the credit risk access. Then, each node makes its own topology graph and builds its own self-centered friendship tree by excluding the greedy node. Lastly, each node uses a friendship tree which is self-centered and fully distributed to allocate a replication.

In [42], heuristics ranking algorithm is proposed for the purpose of identifying and removing selfish nodes (also considered as the one intentionally dropping or maliciously modifying the

content of other nodes packets). This algorithm has three procedures: universal ranking, iterative ranking, and hybrid ranking. The performance of nodes to packet forwarding is provided with universal, while the iteration is incorporated to reduce the false positive ratio. Lastly, in hybrid ranking, the combination of both universal and iterative has been considered. This helps in order to find out the collusion among the participant nodes that reduces the selfish nodes although the functionality of the algorithm is not assessed in the simulation field.

C) Trust and Reputation-based Mechanism

In the network design, trust and reputation mechanisms can be used to detect and eliminate an unexpectedly behaving node. This mechanism gives penalties to nodes with a bad reputation, for instance, excluding selfish nodes from network services for some time.

A utility-based cooperative mechanism is presented for sensor node using the reputation in [43]. This mechanism punishes malicious nodes so that the cooperation between nodes would be encouraged. Three types of nodes' categories would be assumed: normal (nodes that always cooperate), malicious (nodes that always drop the packets of their neighbors) and selfish (nodes that participate in forwarding with some probability). A utility function has been defined according to the reputation value and energy consumption. This function would be calculated as the ratio of the current global reputation value of the node to the initial reputation value, and the ratio of the forwarding energy consumption of the node to the total energy consumption. Then, a model of the mixed strategy of NE solution for two nodes is calculated and further extended to the scenario of multiple nodes interactions. According to its degree of cooperation, each sensor's reputation is evaluated so that the malicious node can be identified and isolated, while at the same time, selfish nodes can also be restricted but not excluded, it can adjust its behavior.

In order to deal with selfishness, a hierarchical trust management protocol for geographic routing algorithm is developed in [44]. The authors also assumed selfish nodes as malicious nodes. Hence, by considering the trustworthiness aspects of social trust and QoS trust, a hierarchical trust management protocol is developed. This maintains two levels of trusts: trust at sensor node-level and CH-level. The peer to peer trust evaluation method leverages the cluster-based hierarchical structure for efficient communications in this trust-based geographic routing. The results of validating this protocol demonstrate that it can approach the ideal

performance level that is achieved by flooding-based routing. However, although message delivery ratio is better, overhead affects this algorithm.

However, in providing secure the network services, a trust management has its own limitations in order to implement. In this management, each node monitors the forwarding behavior of its neighboring nodes in order to detect selfish nodes so that such nodes' packets have not been forwarded by others. In so doing, nodes build trust knowledge about their neighbors. This way, nodes consume their resources to exchange and store such information. In [45], it is studied that the indirect trust information exchanging consumes the scarce energy resource which is increasing with the frequency. In addition to communication overhead, the mechanism of trust and reputation has a shortcoming in which the exchange of information might bring network attacks.

D) Credit-Payment Mechanism

This mechanism is also said to be an incentive-based mechanism. In such mechanism, selfish nodes are not punished or isolated; instead, cooperative nodes are rewarded for serving the other nodes. In [47], by assuming the network consisting of rational nodes, an incentive-based protocol is developed. It adopts the concept of virtual currency (eg., "nuglets") in order to reward those nodes that are participating in packet forwarding for other nodes.

In [48], [49], a secure incentives mechanism to stimulate nodes cooperation is developed. An acceptance algorithm is proposed by using the concept of remunerating the nodes that provide a service, otherwise charging the nodes since they received packet forwarding service. Whether a node has to accept or reject a packet relay request from its neighboring is decided by acceptance algorithm. Each node attempts the algorithm by balancing the number of packets the node has relayed with the number of its packets that have been relayed by others. This scheme results in large packets overhead problems since it also involves per-packet processing.

The limitations in [48], [49] are further improved by [46]. In the latter case, the acceptance algorithm is proposed by using RANDOM and PAY-IT-FORWARD strategies to govern the behaviors of selfish users in relaying traffic. According to RANDOM strategy, each node decides whether to relay traffic to some other nodes or not. In the PAY-IT-FORWARD strategy, on the other hand, each node tries to compare its performance as sympathy for

repaying its debt. As such, the developed algorithm balances the energy consumptions among sensor nodes for relaying the traffic. This algorithm finds a trade-off between energy consumption and session blocking probability. Thus, it takes the decisions at every session rather than per-packet processing. Here, it is emphasized that, since all of such acceptance algorithms are developed based on heuristic concepts, they lack formal frameworks to analyze the tradeoff between network lifetime and packet throughput.

E) Other Mechanisms

In order to detect and punish selfish nodes as well as to determine whether the node is a critical one or not is considered in [156]. To detect selfish nodes, the developed algorithm uses retransmission numbers. Thus, before sending packets each node's retransmission number is recorded within a certain period of time. Then, the average of retransmission numbers for each node is calculated. The node that achieved an average number of maximum retransmission is detected as a selfish node. Otherwise, the node is identified as a normal node since it satisfies the condition of average numbers of retransmission. The process must be repeated until the end of nodes. Lastly, through punishing selfish nodes, replica allocation technique is used to bring selfish nodes into a nature of cooperation with other nodes. That is, to make selfish nodes cooperating with others, simply copying the data items of neighboring nodes into the memory space of the selfish node.

An Incentive Detection Mechanism (IDM) for the cooperation of nodes selfish behavior in WSNs is developed in [157]. It consists of a module for detection of retransmission numbers followed by punishment module. The detection module takes retransmission numbers as the conditions of selfish behavior judgment. It is possible to determine the status of a node by comparing the difference of averaging retransmission numbers and maximum value with the threshold sets. Thus, if it is satisfied, the condition indicates that the node is a selfish one, and if not, the node is a normal node. But, once selfish nodes are known, the punishment module changes the strategies of these nodes into co-operating.

In [158], a framework for the detection of selfishness in multi-hop mobile ad hoc networks is developed. The development is according to Dempster-Shafer Theory-based Selfishness Detection Framework (DST-SDF) with some mathematical background of DSR algorithm. The concept is based on end-to-end packet acknowledgments, i.e., the source node waits for a

certain predefined time for an acknowledgment of the packet, every time it sends a packet to a destination node. The source node has reason to claim that all nodes on the path are cooperative if a packet arrives within the predefined time. Otherwise, the source node knows that there is selfishness on the current path since an acknowledgment does not arrive in time. In this case, a special message recommendation is sent out to inform the other nodes about the situation detected (selfish or cooperative behavior). To evaluate the selfishness of sensor nodes, the received recommendation messages are executed by a single node based on DST algorithm. The resulting values can be used as routing metrics when selecting routes in the next time. When compared to the traditional reputation-based systems, DST-SDF fairly detects all selfish nodes though end-to-end acknowledgments affect its enactment.

In [159], a method to mitigate and detect selfishness in the routing of Disruption Tolerant Networks (DTNs) is proposed. In DTNs, data have to transmit between several nodes based on a store-carry-forward mechanism to access their intermittent connectivity. However, a misbehaving node drops the other nodes packets instead of storing and forwarding. This node is unwilling to share its own memory buffer with other nodes. As a result, system resources such as power and bandwidth are wasted that reduce the delivery of packets throughput. For these selfish behaviors, a detecting scheme that works in a distributed manner has been proposed. The scheme utilizes, an encrypted communication report that it is required to be signed by each node to locally detect packet dropping nodes. Moreover, sometimes it might happen that misbehaving nodes may misreport to hide its history. To detect such nodes, a normal node selects the witnessed nodes and transmits the record summary of each communication report to them. In such a way, with some probability, witnessed nodes will receive two inconsistent communications that help them to detect the misreporting node.

In [160], a delay-tolerant routing algorithm based on node selfishness is developed. The algorithm considers the sensor nodes as social selfishness toward forwarding the other nodes packets. Indeed, it is formulated by using the process of the Markov Chain. In due process, the credibility of each sensor is estimated and utilized for the purpose of selecting suitable packet paths. The selected paths are expected to reduce the transmission delay and increase message throughout.

3.2 Multi-class Sensor Networks

In this section, we present the works related to cooperative packet forwarding in MWSNs. In [17], a payment scheme based mechanism is considered to mitigate the behavior of selfish nodes. The scheme intends to motivate selfish sensor nodes to relay data as well as to ensure the good network performance achievements. The communication protocol selects nodes as mediatory nodes by incentivizing the processes of mediation. In order to transmit data, a node needs to pay, and the payment is discounted for nodes that act as mediators. The payment is also calculated according to the distance this sensor has from the center. The proposed solution has achieved a better performance when compared with the default case communications. Nonetheless, in this mechanism, since incentives are only provided to the altruistic nodes to motivate nodes toward collaboration, if some nodes misbehave, still it may be possible for them to enjoy the other nodes' services without cooperating. In addition, this mechanism is not applicable in the case of resource-limited nodes; its communication would be inefficient. Also, estimating the distance for a mediatory node is not always effective.

A game theoretic model to study cooperation in packet forwarding is presented for multi-domain WSNs in [18]. The BSs are either separated for each user's network or shared across all users. A multi-stage game is used in order to mitigate whether the individual nodes help each other or ignore the possible help they receive from other sensor networks. Such nodes increase the lifetime when they assist each other in transmitting packets; otherwise, to achieve their goal nodes rely on their own network by ignoring the help they receive from others. For each network, two packet routes are established. One route is separately established for nodes that belong to a single network while another route is established in common for all the networks. It is shown that cooperative packet forwarding improves network performance in the case of shared BS, and for separate BSs, the users get the benefit if they provide the service of their BSs for other networks. The work in [18] is further extended into [19], in spite of, their model and simulator are remarkably different. Moreover, in both studies, the cooperation freely happens without any enforcement.

An adaptive energy aware cooperative strategy in forwarding packets in multi-domain WSNs is designed in [21]. Different networks that were deployed for multi-domains have been considered. The topology of sensors is heterogonous and deployed at the same physical

location. The non-cooperative GT based TIT-FOR-TAT strategy is used to develop the algorithm. The strategy is started by generosity, then adaptive energy aware strategy is incorporated to enforce the cooperation between networks and decrease the generosity gradually after each round. Lastly, after several iterations, the networks end up with the cooperation of nodes where individual nodes forward packets for one another. In the simulation, the hierarchical based routing algorithm is used in order to assess the computation of this algorithm. The produced message overhead because of iterated cooperative enforcement might limit its applicability.

The studies in [18], [19], [21] have some restrictions to implement in realities. In these studies, the authors commonly applied the assumptions of classical GT such that strong rationality, complete knowledge, and information about the game and opponents behaviors of sensor nodes. In the reality of sensor networks, such assumptions are impractical. For instance, nodes have resource scarcity to compute these activities in hardcore.

The evolution of cooperation in forwarding packets in static and mobile MWSNs is investigated in [20]. An evolutionary game based iterated N-sensor nodes prisoner dilemma is incorporated. Then, a localized distributive algorithm called Patient Grim Strategy (PGS) is developed at the equilibrium solution. The PGS is defined as “cooperate and continue cooperating until the other player defects n times ($n \geq 0$), then defect forever.” The sum of the payoffs over all periods, which is weighted by a discount factor, gives the payoff to each sensor. At the equilibrium solution, the players can be encouraged to cooperate with their opponent nodes. Otherwise, if the nodes defect for a certain number of times then they would be punished forever (denial of future network services). By using punishment the cooperation is enforced between different classes of nodes. Although the enforcement by means of punishment proved that the PGS has a NE to promote cooperation, the produced message overhead affects the networks. Incorporating the punishment by itself is expensive for resource-limited nodes. Besides, in the evolutionary game, only evaluating the solution of static NE without studying the dynamic evolution would not necessarily bring an efficient solution.

In [150] dynamic incentive mechanism for selfish nodes cooperation in WSNs is developed according to an EGT approach. Selfish sensor nodes have three strategic spaces in the game assumption: sensors provide service all the time (ALLC), sensors never provide service

(ALLD), and sensor R always provide service to ALLC and to other R sensors. In order to distinguish the reputation of each node, the R sensors have to pay seeking reciprocation cost. Under the small reciprocation cost and zero limited mutation probability, the strict NE is analyzed. Mixed nodes' population of ALLC, ALLD and R will finally converge to reach full ALLC nodes. The attain operation has assumed to be an ESS. However, the assumption of selfishness within a single network user to save their resources is unusual. Since such nodes might rather be assumed to be malicious in which the mechanism of incentives cannot handle.

In [22] the cooperation in underwater sensor networks that are governed by different owners is investigated by utilizing the concept of EGT approach. It was aimed to reduce the energy consumption in these kinds of networks for maximizing the network lifetime. The analysis is split into the strategies of non-reactive and reactive nodes where the strategy of nodes would be either to cooperate in packet forwarding or to defect. Then, the simplified model of a game is introduced for cooperation by analyzing both non-reactive and reactive strategies. Hence, under certain conditions, the NEs for non-reactive strategy lead to either full defection or full cooperation. For reactive strategies, to find the best strategy, the current decision is based on the opponent's last moves, and that makes reactive strategy outperform non-reactive one. It is further extended to study the influences of cooperation in given thresholds and the number of sensors per user. However, network resources are easily exploited by lately added non-cooperative networks as the achieved ESS has been weak for some topologies.

In [143] packet forwarding cooperation in multi-hop wireless networks is studied. An Alternating Prisoner's Dilemma based evolutionary model is developed to stimulate an establishment of immediate cooperation. The developed Forwarder Dilemma game considers sensor nodes to adopt the strategies of either Forward or Drop packets. Hence, in every round of packet communication, the strategy adopted by a sensor node would be stored and considered. The strategy that entire nodes have adopted in the previous times would be important for the current decision. So, the proposed algorithm of a repeated game has to decide whether or not a node forwards a packet at a given time. To identify a good standing and bad standing notion of a node, the algorithm uses a memory of storing 3-move interaction history of a node with its neighbors. Nodes choose whether to cooperate or defect in the current round in order to restore cooperation with normal nodes or punishment with selfish nodes. The

evolutionary dominance of the proposed algorithm is proved and it also shows that the algorithm has an ESS. However, storing, extracting or retrieving the interactive history from memory-limited nodes would put the algorithm in danger. In this case, nodes will extravagantly consume their limited resources, which might further limit their functionality.

3.3 GT for Mitigating Selfishness in the Cluster-Based Algorithms

In recent years, GT is widely applied in the designing of cluster-based routing algorithms when nodes are initially non-cooperative. In this context, it has been adopted to mitigate the behavior of these nodes. Its main contribution is to optimize the network capacity and network stability that help to sustain the service delivered. GT based cluster-based routing algorithms are generally classified into cooperative and non-cooperative.

A. Cooperative GT Models

A cooperative based GT is the model that provides each sensor node the opportunity to create coalitions with other sensors by evaluating the obtained benefit. Here, the model prefers to evaluate the network-wide benefit rather than an individual utility. Here, certain proposed cooperative GT models are in the reviewing queue.

In [60] cooperative CH selection of Cost Sharing Game-based Clustering (CSGC) algorithm is proposed. To eliminate the contradiction between cooperativeness and selfishness of sensor nodes, the authors concentrate on the sharing of cost between nodes in coalition head selection. As the cluster members cooperate during both under intra-cluster and inter-cluster transmissions, a bi-directional cooperative clustering model is presented.

Cooperative Game theoretic Clustering (CGC) algorithm is proposed in [61]. It assumes that nodes are self-configured to determine their cluster member on the basis of advertisement signal strength received. It considers a cost-sharing game trade-off between individual and network-wide costs. The number of cluster members, the redundant energy, and the transmission energy is considered in the nodes coalition formation. The cost function is considered to be submodular, and thus, to approximate the Shapley values, a random sampling can be provided within an arbitrary degree of accuracy. As a result, the CGC algorithm suffers in randomizing candidate selection.

Coalitional Game Theoretic Clustering (CGTC) algorithm based cooperative GT is employed in coalition formation of clustering WSNs in [62]. The beginning of the network area is divided

into far and vicinity region. The Coalition Head Nominees, a set of nodes with the highest residual energy in the far region initiated the cooperative game, and then the final coalition is shaped along with other nodes. Lastly, to tackle the energy consumption of data relaying task, some small coalitions are formed in the vicinity region.

In the proposed cluster solution of CSGC, CGC, and CGTC the Shapley value of each node is considered to select the CH. In this case, the Shapley value assigns a single cost to the game of cost sharing. Usually, Shapley value is derived from the solution concept of cooperative GT. In the theory of cooperative games, Shapley value is assumed to be a representative of single-valued solution concept for what is a “fair” way to share the cost of CH workload. Even though the existence of Shapley value has an advantage, it may not be in the core, even for the games that have a nonempty core. In general, evaluating this value is computationally difficult since it has been defined in terms of a formula comprising of exponentially many points of the cost function.

In [99] DEEH cluster-based algorithm is developed for both selfish and non-selfish sensor nodes. The energy levels and transmission radius of nodes are assumed to be different in DEEH. The node with the maximum energy will be selected as the next hierarchy of CH by the algorithm. Then, the CH sends clustering message to other nodes to notify the neighbors to join the current CH. The authors also applied a mechanism to mitigate the behavior of the selfish node that can bring all nodes to act truthfully by revealing their true private information. The true type of node is an input for the mechanism as a vector of strategies, while its corresponding output function is formed as a social choice function. Then, the incentive payment computed by the mechanism is transferred to a node if the node reports its true energy. That means the mechanism will punish those nodes whose objective is to change the social choice objective of the system. Thus, since nodes do not want to receive punishment, they prefer to form cooperation with their neighbors. However, introducing additional punishment into non-cooperative nodes may be costly, and affect network performance. Sometimes such node punishment may even affect the network more than what uncooperativeness does.

B. Non-Cooperative GT Models

Non-cooperative GT based cluster-based algorithms have been proposed for WSNs in recent years. In these types of clustering, the rationalities of nodes in decision-making have been

considered. Hence, each sensor intermingles with the other sensors in the group and optimizes its decisions with the objective of maximizing its own utility.

In [14] CROSS has modeled the problem of nodes behaviors in the establishment of the algorithm. The problem of misbehaving nodes in the cluster formation has been solved using the theory of clustering game. In this game, the node has the strategy of declaring (D) or not declaring (ND) itself as a CH, hoping to receive certain payoff as a result of the game played. In this regard, CROSS has contributed an interesting concept using different theorems that were advanced in GT. At the first round of data communication, every node calculates the probability of becoming a CH. Hence, some nodes choose to be CH and send beacons. The other nodes (that played ND) choose their nearest CH after hearing the announcement. As per zero probability rules, which are set to zero for nodes who have been CH in the earlier round, until all other nodes have also served as CHs. In this manner, the role of CH alternates between sensor nodes. The NE exists where a single sensor announces as D and all others are not, and the mixed equilibrium strategy exists.

CROSS performs better than LEACH in terms of node's lifetime (i.e., with respect to the first node runs out of energy). On the other hand, LEACH is better regarding the last node that runs out of energy. The maximum expected payoff is introduced, also renamed as CROSS2 by slightly modifying CROSS. LEACH is not able to outperform CROSS2, even though it outperforms CROSS for a large number of nodes. The limitations of CROSS is, however, that it is applied to the ideal assumptions that all nodes are simultaneously playing the game i.e., the players are too large. As a result, a node has an extremely small probability to become a CH. Besides, allowing all nodes for the same intercommunication is impossible: they have limited capability, and a longer communication range brings in much packets interference.

CROSS is extended into LGCA in [15] by configuring the nodes to play the cluster game locally. In LGCA individual node can hear transmission signal from its neighbors and the node initially broadcasts a simple 'Hello' message and learns the number of sensors in its neighbors. Then, each node computes its local equilibrium probability to declare itself as a potential CH. All the current potential CHs have to bid for real CH to achieve optimum payoff by ensuring only a single real CH in a certain communication range. Among these potential CHs, the one who first contests the communication media will automatically announce itself as a real CH.

Upon hearing the announcement of the real CH all the remaining potential CHs must return to the normal state and choose their closet CH. In this manner, the NE where only a single real CH and all other sensors are non-CH in the area is attained.

Similar to CROSS, in LGCA the zero probability rule is applied. The latter assumes at a local level to exclude the previous CHs from the process of current CH selection until all its neighbors have served a real CH. The “left-behind node” problem is observed since the CH selection is performed at a local level. It is solved by using two assumptions. The first assumption is allowing all left behind nodes to become potential CH and bid for real CH through MAC contention, while in the second case the left behind node increases their communication power level to join the existing CHs. The former is called as LGCA1 while the latter is called as LGCA2. To some extent, in terms of an average network lifetime, both LGCA1 and LGCA2 achieve better than LEACH and CROSS. Even though in LGCA the CHs distribution is uniformly scattered, the energy dissemination among the nodes could not be balanced. It only considers the probability of nodes selected as a CH rather than the important parameters (such as energy). However, since nodes are battery-operated, the remaining energy of each node would have to be evaluated for a better improvement.

A cluster-based routing algorithm called CORE is proposed in [16]. GT is used to determine the cost and reward of being a CH and formulates the probability of a sensor node to declare as a CH. A virtual reward is given to CH nodes to encourage nodes to become CHs. On the other hand, to minimize the number of CHs it is assumed that the reward is smaller than the cost. NE is analyzed in due process where only one sensor declares to be a CH while others restrain from declaring themselves as the algorithm is distributed. The achieved equilibrium considers both pure and mixed strategies of nodes. At each round the nodes calculate their own probability to play as a CH. The probability of a node to be a CH in CORE is determined by the value of cost (coupled with residual energy) and reward parameters. As a result, nodes with high residual energy have a low cost of being CH and nodes with low residual energy have a high cost of being CH.

The performance evaluation of CORE is between CROSS and probability based clustering method. It can balance the two clustering methods. Like that of CROSS, CORE assumes that the CHs selection procedure is based on the game played between all nodes. However, it is

impractical to consider, particularly for large-scale sensor network architectures, since the nodes have restricted transmission capacity. Besides to this, the rewarding concept that is included in the algorithm affects its functionalities, in which the memory-limited node is incapable to store and compute such additional indicators.

A game theoretic approach is proposed by investigating non-cooperative hedonic clustering game in [64]. As such, two clustering models such as fixed and correlation are developed. To maximize their utility function, every selfish node as the player makes a decision to join a cluster. Hence, the resulting clustering is the outcome of the choices of all sensors. The comprehensive theoretical analysis of clustering game using a mathematical method is the very important contribution of the works, though not supported by simulation analysis. In addition, its performance has not been compared with other algorithms.

A repeated game theoretical approach with limited punishment mechanism for clustering in mobile ad hoc networks is proposed in [69]. The included punishments prevent a node from playing the “dishonest” strategy and reporting a deceitful weight value in the cluster-based algorithm. By doing this, all nodes will act honestly and further guarantee the correctness and fairness of CH election. In that manner, each node is assumed to have a weight value composed of residual energy, average moving speed and connectivity with its neighbors. Then, a node having the lowest weight value is chosen as a CH. The simulation was not conducted in order to compare its performance with others. Including the “watchdog” into a resource-limited node to detect the actions of its neighbors is unusual. In such case, node is unable to execute the punishment operation.

A GT based clustering approach for selfish sensor nodes is proposed in [63]. It adopts data replication to increase throughput in case of network disconnection. The authors assumed that the network is composed of uniformly dispersed selfish nodes within a circled field and the entire network is divided into $k = 5$ equal clusters. Hence, any node with the maximum residual energy in a cluster is chosen as a CH. In this regard, the network can survive for a longer period of time by changing the CHs roles periodically. To promote cooperation of nodes, the CH declaration is regarded as a game, and it adopts a game-theoretic model. The idea of another node as candidate CH is included despite the current CH in order to overcome losing data. All member nodes except the current CH would participate in the method of candidate CH

selection. Thus, in order to win the possible payoff, one node has to turn into a candidate CH. When the communication between the current CH and the BS fails, the BS can continue receiving the replica of data from the candidate CH located in the same cluster. As a result, the robustness of the network is improved. However, the applicability of this algorithm is limited to when there is a possibility of network division. In addition, having two nodes (CH and candidate CH) at a time of packet transmission is infeasible in the context of sensor nodes.

In [67] the authors proposed ACHGT which is a centralized algorithm where CH selection and the number of clusters are decided by the BS. This decision is based on the information of nodes' location and the remaining energy. In this algorithm, the individual nodes are also players to make decisions. Whether the selected node becomes a CH or not is determined by using the nodes' energy payoff functions, in that the node would weight its own costs and benefits to be a CH. Though this way of a CH selection is energy-efficient than a random one following the LEACH algorithm, its centralized operations still consume an additional energy from each node due to the excessive overhead in the process. No theoretical analysis has also been provided for this algorithm. The applicability has been restricted to the aspects where nodes are equipped with location detectors such as GPS.

A centralized TEER (Trustworthy Energy Efficient Routing) algorithm is proposed in [68]. The algorithm aims to increase path security in hierarchical cluster sensor networks by distributing energy consumption evenly across sensors. A trust model is incorporated in order to evaluate a node's trust level and detect malicious nodes. The malicious nodes are the sensor nodes that are misreporting, modifying and dropping data packets. At the very beginning, each node's trust level is initialized to 1, i.e., it is assumed that all nodes are trustworthy. Note that, the range of trust level is between [0-1]. Each node stores locally a copy of its own trust value. In addition, the BS can also store and evaluate centrally the trust value of every node. The BS has to dynamically update each node in order to maintain the consistency between the locally stored trust value of each node and its equivalence trust evaluation stored in the BS. The BS uses an ACK message during this updating. When a node's trust level is below a certain predefined threshold, this node will be confirmed to be evil and it will be added to the blacklist and isolated from the CH election.

The NE of CHs selection is developed using a game theoretic paradigm. It is assumed that each node's payoff is equal to its CH's payoff value, in that it is calculated based on energy level, trust level and average path loss within neighboring nodes. Accordingly, each node tends to select a neighbor with maximum payoff value as a CH to maximize its payoff; otherwise, any other results will decrease a node's payoff utility. In addition to maintaining and updating all nodes' trust evaluation result, the BS is responsible for maintaining the clustering information, recording each cluster's CH and member nodes. In TEER, misreporting can only occur at source nodes while data packet modification and loss can only occur at the CH level. The results testify that this algorithm produces a safer network and longer network lifetime. However, as selecting the CH node is based on the ACK information of the BS, trusting the BS itself is one of the drawbacks of this algorithm. In addition, listening repeatedly the information that is centrally broadcast by the BS also limits the functionality of nodes. This also brings a message overhead into the networks.

In [65] DEGRA is developed in order to resolve the resource conflict between sensor nodes in transmitting packets. In this aspect, the GT helps sensors in making a rational decision. The algorithm sets a utility function for every node by computing the density of the nodes, residual energy and average energy consumption of neighboring nodes. According to theoretic game model, specifically, CH selection turns into a procedure of nodes' decision making. In due course, the node with the larger utility function can be selected iteratively. Also, by using an approach of greedy geographic forwarding, the intra-cluster and multi-hop inter-cluster routing mechanism is designed. The results show that the proposed routing algorithm does consume less energy when compared with probabilistic based LEACH. Yet, the assumption of nodes rationality for a decision making would be uncommon, in which the CH selection procedure would be affected by a decision made.

GTRF [66] is proposed in order to address the problem of massive packet loss due to the nodes' selfish behavior or VOID regions (a node has no neighbor to forward the packets) has been solved. GTRF constitutes of two parts: the cluster forming with Vickery Auction (VA) model and the packet forwarding. The behaviors of nodes (i.e., selfish and normal) are modeled by using VA model. Selecting and regulating the strategies of fault tolerant nodes to bid for becoming CHs. In this model, the situations of bidding strategies in each cluster are proved to

reach a NE. In the VA model, the auction is taken within clusters. In this regard, in each round of CH selection, each node (including the current CH and cluster members) in the cluster can bid its actual remaining energy for next CH. Then, the node with the highest bidding value will be designated as CH in the next round. The packet forwarding procedure establishes multiple circular transmitting paths to guarantee real-time transmission, and also it helps to avoid the impacts of the VOID regions. The performance of GTRF shows that it can efficiently balance the energy cost of the network and thus prolong the network lifetime.

C. Other Types of GT Models

The theoretic analysis of an evolutionary game is applied for developing the cluster-based algorithm in [149]. The asymmetrical distance of each CH from the BS and the remaining energy of each node are considered for strategies investigation. Two areas of the region where the sensor nodes would be deployed are regarded as the players. These areas are adopted into the strategies of the CH selection to optimize the energy of the nodes. ESS is analyzed assuming the territory and the war of energy attrition game. In order to define the area limits in the sensor deployment region, the Territory Game based Clustering (TGC) algorithm is derived from the territory game analyzed. The nodes may have several probability levels in order to be assigned as CHs based on their region of location.

An unbalanced energy consumption of nodes that is caused as a result of asymmetrical distance from the CHs to the BS is also mitigated using TGC. The war of energy attrition game is analyzed normally with the purpose of deriving the War of Energy Attrition Clustering (WEAC) algorithm. The probability of a node becoming a CH is determined by WEAC: depending on its available power resources as well as the strategies of the opponents. However, except the theoretical aspect is a bit presented, the evolutionary game lacks details (eg., the achievement of the static ESS).

Game Theoretic Energy Balanced (GTEB) based geographical routing protocol for WSNs is developed in [148]. Two-level combinations of EGT and CGT are used. In order to balance communication energy in GTEB protocol, both region level and node level energy balancing mechanisms are provided. It is assumed that all nodes know the location and are homogeneous with a transmission region. In order to decide the role of nodes in the routing algorithm, similar to HBDR [112], the GTEB protocol uses two types of games. In HBDR, the games are used for

the purpose of tree formation, whereas in GTEB the games are played among the nodes to make the decision between sender and forwarder region nodes. First, based on network density, the transmission region around a sender node is divided into a set of forwarding regions (sub-regions) using EGT. Then based on the available energy of these sub-regions, the amount of traffic to be forwarded to those regions is determined by EGT. Finally, from the forwarding region, one potential forwarding node is selected using CGT to send a packet. The CGT balances the energy at node level that prolongs the network lifetime by providing a better packet delivery ratio. However, being a geographically based routing, nodes need to know their location, which further consumes nodes crucial energy.

In [161], a game theoretic approach for CH selection algorithm is proposed to enhance the survivability of WSNs. It is based on the distance and the internal energy of nodes. A game of scheduling the nodes is an interactive decision-making process between a set of self-interested nodes. A Fuzzy-c algorithm means of clustering approach is applied to find the initial clusters along with member nodes. The Euclidian distance from the BS to each static node is calculated, followed by calculating the energy consumption of sending and receiving packets. The payoff of each node in the cluster is calculated to determine the node with a minimum payoff as a head node for every cluster. In every time interval, the total payoff for nodes in the cluster is calculated to justify that the system is stabilized with the current selected CH. Otherwise, the system goes to the new CH selection phase since the total payoff of a current CH falls below the threshold value.

A centralized cluster-based algorithm is developed using differential game [70]. Accordingly, the payoff value of the differential game called forwarding contribution is proposed by which selfish avoidance was utilized in the clustering. Since selfish nodes report their residual energy untruly, the theoretic game is included to avoid these nodes from miss reporting. In this case, there is no opportunity for these nodes to show their selfishness. The virtual currency value of forwarding contribution is also provided to select the CHs. Thus, the connection between different CHs (in CHs-to-CHs) is theoretically analyzed. However, the overall topology of the network is still managed by the central BS. Thus, pre-assigning the position of the nodes would be required which might be difficult. In this scheme, the nodes always have to listen to the BS, which might affect the nodes' communication.

In [162], a clustering scheme is proposed to improve the energy utilization of nodes using both cooperative and non-cooperative GTs. Selecting the node having a sufficient residual energy and high trust level as a CH is what is suggested in this scheme. In the selection scheme, each node computes its respective payoff value in that the node having maximum payoff within neighbors will be selected by winning the game. In this scheme, the assumption about the rationality of the sensor nodes is not resolved yet. In addition, it lacks the details of how each node interacts to share the information about the game. In [71] GT based Nash bargaining solution strategy is applied in the cluster-based routing algorithm design. Its aim is to allocate the communication resources of selfish nodes in the course of cluster formation. Energy consumption of cluster members has been modeled using Nash bargaining the strategies.

Other than the GT approaches discussed above, there are other available methods (such as reputation and trust framework) for developing algorithms. A number of trust and reputation mechanisms have been studied in order to control the behaviors and the activities of selfish nodes. In [52] an efficient invulnerable CH election model is addressed to handle selfish nodes. In this scheme, the rate analysis value is incorporated to capture the behavior of nodes that could not voluntarily accept the CH role. It is updated for every round to encourage nodes to honestly participate in the CH selection. According to the energy of each node and its link quality with the BS, a rate analysis value of a node is estimated to decide whether a node will participate in the CH selection or not. In the selection, the node which has the lowest rate analysis value participates, and finally, the head node is selected in the cluster-based algorithm on the number of votes it gets from other nodes. To that end, it is proved that to avoid the CH to become selfish, the scheme balances the resource consumption of CH and its members.

In [104], a security framework for cluster-based WSNs has been proposed when individual nodes in the cluster become selfish (also called passive attack or inside attack), in the intention of saving their resources. In designing the framework, two special nodes per cluster are incorporated: CH and Inspector Node (IN) that work in a specific way in addition to some ordinary nodes called Member Nodes (MNs). To restrain the selfishness of nodes in the whole cluster, reputation scheme is adopted. The IN exploits packet overhearing of CH's transmission. Thus, if it finds some problem in an overhearing, then it blacklists the current CH and also informs MNs within its range to stop sending their data to that CH.

The MNs also evaluate their own reputation system to refuse the IN's decision, just in case when it deliberately accuses a CH. Temporarily a CH also ascertains its status by sending random checking requests to IN. Besides, bad reputation values are assigned by CH on those MNs that refused in IN nomination part for a long time to save their energy. Three levels of strategies were developed to fight against the selfishness. The uniqueness of the clustering process is shown as the first level, which incorporates a CH and an IN per cluster. The process of clustering is carried out in two rounds in order to obtain the topology of the cluster consisting of CH, IN, and MNs. The second level shows the role of the reputation scheme contributing to the other two levels and the third level reveals specific operations at CH, IN, and MNs besides their usual activities. It is shown that, by controlling selfishness, the algorithm has been improved so that it becomes more consistent and resilient.

In [105] cluster-based reputation and trust framework is developed for WSNs. It is developed to prevent the selection of compromised or malicious nodes from CH selection. To drive the selection of the next CH, a reputation metric based on successful and unsuccessful network events is communicated between the cluster members and the current CH. The current CH activates the election procedure when a certain threshold (e.g., battery levels) is reached. In the end, a CH is selected according to the majority of votes and through a key exchange procedure if it is ensured that it is not a compromised node.

In [106], a lightweight and dependable trust system has been proposed for a cluster-based algorithm to reduce the effect of malicious, selfish, and faulty CHs. The role of nodes identity within clusters is protected by the scheme of lightweight trust decision-making that applies the feedback cancellation process between misbehaving cluster members or between misbehaving CHs. A dependability-enhanced trust evaluation is considered to establish co-operation between CHs in transmitting data.

3.4 Summary

In distributed sensor networks, misbehaving nodes have been the real problems since they badly affect the performance. As discussed in this chapter, too many approaches are there to mitigate with their behaviors in particular for ad hoc networks. However, if we consider the resource-limited sensor nodes, no approach provides an efficient solution to the problem, especially if we consider MWSNs. Consider a credit-based approach that has been discussed. It

provides incentives to the normal nodes to bring the whole nodes toward cooperation, however, for selfishly behaving nodes without cooperating with others still they might be possible to enjoy the services of other nodes. As a result, in this kind of solution models, the limited resources of honest nodes are always exploited that actually causes the malfunctioning of the services provided by networks.

In the trust and reputation mechanisms, once a bad reputation node is identified by other cooperative nodes, a penalty of not using other nodes' network resources is provided. It is also noted that in these mechanisms, though the node is working honestly, sometimes certain nodes deliberately accuse the other nodes. In such case, the whole nodes come to learn and develop a bad reputation value for this node thus, decided to blacklist it. However, excluding an important node from the network services usage by developing a wrong perception is sometimes might even affect the network more than the way a real selfishness effects.

Detection and isolation mechanism is also following a way to penalize selfishness, i.e., misbehaviors isolated from receiving any network services. However, detecting and isolating itself can be costly for resource scarcity nodes. In this scenario, the communication channels need to be monitored. For instance, to identify these nodes, a normal node has to listen to the channel and/or process the information sent by the misbehaving nodes. The listening and processing consume the resources of a normal node. On the other hand, if many nodes in the network selfishly act (for instance, assuming nodes belong to MWSNs), and all of them are isolated, thus, the whole network communication might fail to function.

Thus, this hints to us that all selfish nodes cannot necessarily be eliminated, as there might be situations where they can be kept and used in the network. Therefore, a mechanism has to be developed for the coexistence of normal and selfish nodes without the normal nodes harmed by the other misbehaving nodes.

The research methods of establishing mutual cooperation between nodes of MWSNs have also discussed. Most of the available methods used the rationality of nodes in the GT approach. Each node as a participant player of the game needs to analyze its intelligent rationalities of whether to forward the packets of its neighboring nodes or not i.e., the methods concern toward looking for best actions of the individuals' nodes. Hence, the different decision makers nodes should reach and recognize the stable outcomes for the benefit of multi-class networks.

In addition, numerous models proposed for non-collaborative setting nodes with respect to establishing the cluster-based routing algorithms were assessed. This aims to analyze the contributions and shortcomings made in the categories of clustering schemes. As discussed above, the amount of game theoretic models dealing with nodes selfishness for the cluster-based algorithm is tremendous. Yet, they have several drawbacks in relation to the dissertation's objective. These theoretic models are not directly applicable with respect to the characteristics of resource-limited sensor nodes. In addition, these models are too specific or provide too general analyses for cluster-based routing algorithm. Accordingly, the given models are not suitable for the dissertation's framework and not satisfying for our research challenges.

In contrary to other game theoretic models, the theory of the evolutionary game is assumed the bounded rationality of the nodes which is in line with the characteristics of nodes in sensor networks. With its limited rational capabilities, the idea of using this dynamic evolution over other theories was given more attention for owing the nodes resource constraints. The evolutionary games found only little application in distributed sensor networks, and a directly suitable work is not available. Nevertheless, after some adaptations are made it can be used as the best solution approaches, the evolutionary game model fits well to the dissertation's methodology.

CHAPTER FOUR: NODES COLLABORATION WITH EVOLUTIONARY DYNAMICS

In Chapter Three, we have seen that individually owned resource-constrained nodes act non-cooperativeness in transmitting the packets. Their aim is to save their communication resources. Besides these, we have discussed the limitations that the previously developed methods are faced while dealing with these nodes since they affect the sensor network performances. In this chapter, we approached these challenges using an evolutionary dynamic model. Accordingly, the outcome of sensor networking collaborative equilibrium is addressed. To that end, the proposed cluster-based packet routing is considered to analyze the model.

This chapter is organized as follows. An overview of MWSNs collaborative designing will be introduced in Section 4.1. Section 4.2 introduces a model of mutual collaboration whereas its evolutionary dynamic development will be presented in Section 4.3. In Section 4.4 the dynamic system of our model is analyzed and its incentive-based collaborative equilibrium is computed analytically and using numerical simulation. Accordingly, packet forwarding schemas (for collaborative and non-collaborative nodes) are proposed and its simulation results are discussed in Section 4.5. Eventually, the summary of the chapter is drawn in Section 4.6.

4.1 An Overview of Nodes Collaborative Designing

This chapter aims to design a representative model in order to capture the behaviors of non-collaborative nodes in designing routing algorithm. As such, a theory of EGT approach has been taken so as to develop an ECG model. The strategy of nodes' population adapts and converges to ESS equilibrium by considering the outcomes in the interaction state. Such equilibrium has been considered in line with an evolutionary process of replicator dynamics: dynamic natures that can model and capture the adaptation of nodes in which nodes change their strategies over time and reach stability equilibrium. In this stage, an individual node starts to share a communal strategy in communication.

The concept of evolutionary dynamics is well-documented in the biological sciences. Our proposed sensor networking model has some common characteristics with the assumptions of biological science. In both cases, the modeled system has the behavioral aspect as well as

physical representation [59], [126], [145], [146], [147]. The behavioral aspect is a distributed nature of perhaps, non-cooperative nodes' or agents' interactions. While randomly interacting with each other in the large population, such entities make a decision that benefits them. Besides this, in a physical representation, both of them depend on the central resources, such as energy and other physical components to sustain their life. Thus, their survival can also be determined in relation to their resource conservation. From this perspective, both the model assumptions need to protect the internal resources of nodes or agents in the vicinity (eg., the fittest individuals should survive and reproduce for the next interaction, while the least fit should die off, corresponding to Darwin's theory of evolution).

Hence, the model that was designed was conceptualized and developed along with the works of [30], [31], [59], [114]. The model has been built by considering the mapping of several aspects in routing packets. In this case, the non-cooperative nodes have been mapped into the players (or the replicators also called the agents) of the evolutionary game. In a given game of instance evolutionary mechanism, each node randomly participates with other population of nodes by taking certain strategies. Accordingly, the communication behaviors of nodes are mapped into either 'Cooperate' or 'Defect (non-cooperate)' strategies whenever required. Then, the convergence of replicator dynamics is analyzed as an Evolutionary Snowdrift Game (ESG). So, a pair-wise contest game of two nodes that participate in the game of packet forwarding is modeled as a two-player ESG. Correspondingly, the effect of multi-sensor nodes' population is also modeled as an N-player ESG. In this way, the designed model can be generalized for the enrichment of collaborative equilibriums between nodes. Then, this dynamic equilibrium can be used in the designing a routing algorithm.

Our proposed model is meant to resolve the issues of nodes' non-cooperativeness. It considers the fitness of resource-limited nodes in the state of evolutionary dynamics in which node adjusts its strategies of forwarding packets by reacting to a simple observation to other nodes. From this perspective, the strategy adjustment of nodes is expected to reach the dynamic equilibrium in which they receive a shared benefit for adopting that strategy. Thus, to keep their state of fitness, these nodes need to adjust and build their responsive strategies through adaptation process such as through adaptive learning. In this manner, in the course of packet routing, the individual node has the chance to balance its resources, in which it extends service

qualities. Thus, the proposed model has the capability to preserve and manage communication resources.

Collaborative equilibrium aims to mitigate the behaviors of uncooperative nodes according to the introduced rewards in addition to the other payoff functions. By assuming that these nodes interact with each other as a population in the evolutionary game, the common steady equilibrium is analyzed for the entire nodes. Accordingly, it moderates and brings these nodes to a state of common equilibrium even though they are large in numbers. This is shown by analyzing the behaviors of equilibrium, both theoretically and numerically, with respect to the payoff function and the number of collocated nodes. Providing an incentive mechanism greatly encourages the nodes in the direction of reaching a global equilibrium which is also the same for all nodes that operate in that vicinity. At this state, therefore, individual node prefers to establish a collaborative framework.

Finally, the concepts of this equilibrium will be extended to the development of the routing algorithm. As such, a cluster-based CPF algorithm is proposed: nodes collaborate with each other in forwarding packets since they are highly concerned about the obtained benefits. Thus, the performance of cluster-based CPF is compared and evaluated with the default cases, otherwise, called NcPF algorithm. The latter is proposed based on the general assumption of communications where nodes cannot cooperate. Thus, through studying systematic simulation, it has been shown that CPF optimizes source utilization. Unlike the default one, CPF achieves better network lifetime due to the achievements of mutual packet forwarding.

4.2 A Mechanism of Mutual Collaboration

In the MWSNs, the task of forwarding packets requires the mutual cooperation of collocated nodes. Sharing the communication workload is important for these nodes in order to conserve their resources. When a strategic adjustment and a cooperative agreement is reached between them, such nodes honored their communication energy for transmitting packets (for instance, the energy that is acutely consumed in the course of a longer range communication is avoided).

4.2.1 Representation of an Evolutionary Approach

In this dissertation, a GT mechanism is proposed in order to deal with the contexts of misbehaving nodes. For this purpose, an extended version, otherwise known as EGT, was

adopted to foster the strategies used by these nodes. In other words, this model is provided to identify and mitigate the behaviors of these nodes. In this mechanism, differently-owned nodes interact to get the information about their opponent's activation and update their strategies. Accordingly, they have to enter into a stage of common benefit. By updating their strategies dynamically, the evolution of collaborative equilibrium will be established between these nodes as they agreed to work together in forwarding packets. In this evolution, the framework of packet forwarding is, therefore, the joint strategy of any collocated nodes in that region.

With respect to the assumptions of rational nodes behavior as well as the possibility of stable strategy states, an evolutionarily based modeling has considerable advantages over the classical GT. In EGT the rationality of nodes would be bounded unlike the other. In this consideration, individual nodes adopt suitable strategies through practicing or being pre-programmed with a set of actions to be performed so as to share with other without any modification. Accordingly, resource constraint nodes update their strategies of interactions in the meantime. This means, by simply analyzing their actions and payoffs, they learn how to adapt and execute well. The static stable state of evolutionary modeling also serves as a refinement to the ordinary equilibrium concept that was used in the classical one.

We assume that each node updates its own strategies based on the benefit obtained in the latest rounds of interactions with peers. In many multi-agent systems of practical relevance, this is expected to bring the population of nodes towards an ESS. If all members of the population adopt ESS, then the statistical distribution of the strategies does not change. In other words, no mutant strategy could invade the population. The approach taken by the present work towards nodes' selfishness consists of designing an evolutionary mechanism that brings them to collaborate, so as to improve network performance.

4.2.2 ECG Model

Here, we begin by formally presenting our model, which can be defined as an **Evolutionary Collaborative Game (ECG)** $\equiv \{N, S, U\}$. The players of the game are selfish sensor nodes that denoted by $N = \{1, 2, 3, \dots, n\}$. Assume that their actions are organized into rounds. A node player, at each round, can adopt a strategy from the strategy space $S = \{s_C, s_{Nc}\} \equiv \{C, Nc\}$, where C corresponds to bidding for a collaboration in packet forwarding, and Nc corresponds to not bidding for a collaboration in packet forwarding. At a given time, a node adopts either C -

strategy or N_c - strategy. For the sake of brevity, hereafter, such nodes adopting strategy s_C are called C-nodes; those adopting strategy s_{N_c} are called N_c -nodes.

The set of utilities or payoffs that the sensor node receives while participating in the ECG model is represented as $\mathbf{U}$. It measures the level of each player's satisfaction if its strategy space gets realized. For instance, if the data sensed and then sent out are successfully relayed by the other nodes to the BS, the source node experiences a positive payoff. This payoff is computed using variables b and c , ($0 < c < b < 1$): where b is the benefit obtained by a node as a result of its packets reaching the intended destination, and c is coupled with the energy and the other resources consumed in the course of sending the packets. The payoff of any node depends on the strategy of that node itself as well as the strategy of other nodes in which it currently interacts with.

A node can collaborate in forwarding the other nodes' packets to the BS or to other nodes; otherwise, a node cannot collaborate by not forwarding, (i.e., dropping the data packets of other nodes). In any case, however, each node might forward its own packets to the destination. Yet, this is unattainable for nodes due to their limited communication resources. These battery-driven nodes might reduce the service quality in such packets communications. Hence, for nodes, it would be advantageous to collaborate.

In our ECG model, additionally, the following simplified assumptions have been made about nodes that participate in the game:

- Sensor nodes are “bounded rational” and large in number.
- All sensor nodes are equivalent and have identical payoff matrices (are playing a symmetric game).
- Sensor nodes randomly interact with equal chance and are capable in each round.
- Based on the average success rate of a strategy an update can be made.
- All sensor nodes use the same strategy update.

4.3 An Evolutionary Dynamic Model

As already stated, our proposed evolutionary dynamic model is built around the replicator equations. The model assumes the dynamic behaviors of collocated nodes. Thus, in this section, first, its derivation process is shown step by step.

Then, by applying the derivation in several distinct ways, the major characteristics of our model is explored for sensor nodes. An equilibrium solution of our dynamic model is also studied for two-player nodes. Lastly, the alternative scenarios of multi-players competition game have been considered in order to address the interactions of a very large number of nodes.

4.3.1 Dynamic Equation

In this model, a dynamic equation is adopted from a standard equation of replicator dynamics [51], [118]. It is a structured pattern that must be monitored by a set of nodes. Nodes interact with other nodes to establish a relationship in forwarding their packets. With the objective of achieving, and then monitoring the collaborative relationship, a replicator system of evolutionary dynamics is required to be developed. This system will monitor the frequency distribution of collaborative nodes that are represented in the network region as the round of packet transmission changes over rounds.

Hence, the objective of applying the evolutionary dynamics in MWSNs is not to study the strategy of the individual node. Instead, it is with the objective of studying and developing the dynamic system that controls the strategy and the relative shares of the nodes' population. Initially, these nodes are pre-programmed as having dissimilar characters in the collocated sensor field. In this regard, by using a methodology of understanding and then building on it, the set of these nodes will try the available strategies to obtain a benefit in each round of packet sending. From these strategic interactions and the benefit obtained, the set of nodes learn the behaviors of other nodes. It will repeatedly be executed by the subpopulation of nodes since nodes are initially unsure of others action and utility.

With this regard, our main task will be to present how the replicator dynamics can arise between non-cooperative nodes. Hence, given an evolutionary dynamics, individual nodes use only pure strategies, $S = \{s_1, s_2, s_3, \dots, s_{|S|}\}$. Let us assume the actions of the nodes are organized in rounds. If n_{si} denotes the number of sensor nodes using s_i strategy during a given round, then the total sensor population size, $N = \sum_{i=1}^{|S|} n_{si}$ and $x_{si} = \frac{n_{si}}{N}$ is the proportion of nodes that play a strategy s_i . The overall state of the population during a round is described by the vector, $x = \{x_{s1}, x_{s2}, x_{s3}, \dots, x_{si}, \dots, x_{|S|}\}$. Also, let α and μ be the time scale of node population

growth or decline rate for playing particular strategies, respectively. Assume also n_{si}' as the rate of change of individual nodes that are using s_i strategy.

Then, we have

$$n_{si}' = (\alpha - \mu + U(s_i, x))x_{si}N \quad (i)$$

where $U(s_i, x)$ is the instantaneous average payoff of the individual node that is using pure strategy s_i at time t , in an alternative way it might be also represented as $U_{si}(x)$ in this dissertation.

It is given that, $n_{si} = x_{si}N$, therefore, the above equation is rewritten

$$n_{si}' = (\alpha - \mu)n_{si} + U(s_i, x)n_{si} \quad (ii)$$

Let us also consider N' as the rate of strategic change of total sensor nodes' population, then

$$N' = \sum_{i=1}^{|S|} n_{si}' = (\alpha - \mu) \sum_{i=1}^{|S|} n_{si} + \sum_{i=1}^{|S|} U(s_i, x)n_{si} \quad (iii)$$

Then, by substituting, $N = \sum_{i=1}^{|S|} n_{si}$ and $x_{si}N = n_{si}$ respectively inside the first term and the second term

$$\begin{aligned} N' &= (\alpha - \mu)N + N \sum_{i=1}^{|S|} x_{si} U(s_i, x) \\ &= (\alpha - \mu + U_{avg}(x))N \end{aligned} \quad (iv)$$

where, $U_{avg}(x) = \sum_{i=1}^{|S|} x_{si} U(s_i, x)$, an average payoff of the whole population of sensor nodes.

Since $n_{si} = x_{si}N$, we have, $n_{si}' = Nx_{si}' + x_{si}N_{si}'$, thus,

$$\begin{aligned} Nx_{si}' &= n_{si}' - x_{si}N_{si}' \\ &= (\alpha - \mu + U(s_i, x))x_{si}N - x_{si}N(\alpha - \mu + U_{avg}(x)) \end{aligned} \quad (v)$$

The constant factor $(\alpha - \mu)$ merely changes the rate of adjustment to the stationary. It simply leaves the stability properties and trajectories of nodes' population at a dynamic system of the unchanged state. Furthermore, we are interested in how the population of each strategy of

nodes changes over time, by assuming that nodes have uniform interaction rates. In this regard, nodes will interact with each other in the network indiscriminately, hence, the constant factor in the above equation will be $(\alpha - \mu = 0)$. This means the time scales can be omitted.

Thus, by canceling N from both sides of the above equation so as to consider the continuous time limit, we obtain the following evolution equation for our dynamic model.

$$\dot{x}_{si} = x_{si}[U(s_i, x) - U_{avg}(x)] \quad (4.1)$$

where $\dot{x}_{si}$ on the left-hand side denotes the time derivative of the proportion of the population adopting strategy s_i .

The provided replicator dynamics analyzes the strategic adjustments of nodes in the population. Individuals adjust their strategies according to their relative shares of advantages. Considering to Equation 4.1, the core of this replicator dynamics has the following assumption. If adopting a strategy represents an advantage, in terms of payoff $U_{si}(x)$ with respect to the average payoff $U_{avg}(x)$ of the whole population, then the players will tend to adopt that strategy: as a consequence, its share will increase in the next round, and the reverse also holds true. In other words, the proportion of individuals that are using strategy s_i increases if their payoff is bigger than the average payoff of the whole population; otherwise, they need to decrease as their payoff is smaller. This equation will further be used and analyzed in this dissertation.

A fixed point of an evolution at which also some stability conditions are fulfilled is assumed to be an ESS, (i.e., at ESS $\dot{x}_{si} = 0$, for all s_i). These stability conditions will be expressed in terms of second derivatives, which are presented in the next section. Accordingly, the steady-state, otherwise, called stable equilibrium has been specified both analytically and numerically.

Concerning this replicator dynamics that has been employed in this dissertation, several points are worth mentioning. First, in this model, the frequency distribution of nodes' strategy increases when it has a payoff above the average. This means this equation is not accompanied by a best-reply strategy to represent the behavior of nodes, i.e., the "rationality" of individuals is not required like the one in classical GT. Nodes in our assumption have very limited and localized information concerning to the network as a whole. Thus, for the response of strategic distribution of the previous round, adopting the best reply is not possible for them. Hence, the "bounded rationality" of nodes should always be held in our model.

Second, if we sum up all the equations of x_{si}' over s_i strategy, we get $\sum_{s_i} x_{si}' = 0$, as a result, at one point in time if $\sum_{s_i} x_{si} = 1$, it remains true forever in the evolution. Moreover, although a particular node can vanish as $t \rightarrow \infty$, a node that is not represented in the population of nodes at one point in time will never be represented at any time later, i.e., new nodes are not created in the due process.

Third, it is assumed that nodes would not make “mistakes” when switching their strategies in the majority of cases. That means nodes rarely switch from a better payoff strategy to a worse. The number of nodes should be taken into account in our replicator equation to analyze how nodes exchange their strategies. An arithmetic mean of nodes is vital in the system to average over the possible behaviors of a node. Accordingly, a system will be obligated by the dynamics in order to increase the frequency of a strategy with an above average payoff. Although there might be nodes that switch from better to worse, on average, it is assumed that the ones that stick to the better payoff will outnumber them in the nodes population.

4.3.2 Pair-wise Contest Game

In this section, we address the problem of finding the dynamic equilibrium when two-player interacts. Let us consider a simplified version of ECG model where two nodes participate, i.e., a pair-wise contest game. Since the strategy space of our ECG is $S = \{C, Nc\}$, the proportions in the population are indicated by x_C and x_{Nc} , with the normalization condition $x_C + x_{Nc} = 1$, i.e., model has only two pure strategies. The overall state of the population is described by the vector $x = (x_C, x_{Nc})$. The replicator dynamic equations are

$$\begin{aligned} x_C' &= x_C(U_C(x) - U_{avg}(x)) \\ x_{Nc}' &= x_{Nc}(U_{Nc}(x) - U_{avg}(x)) \end{aligned}$$

However – thanks to the normalization condition – the whole dynamics can be expressed in terms of a single degree of freedom $x_C = (1 - x_{Nc})$ as

$$x_C' = x_C(U_C(x_C) - U_{avg}(x_C)) \quad (4.2)$$

The normalization condition guarantees that other equation will be given by $x_C' = -x_{Nc}'$.

Now we formalize our assumptions about the utilities U_C and U_{Nc} . We assume that they are determined by the benefit a node received (b) and the cost in which a node incurs (c). The cost

is always lower than the benefit coming from a successful message delivery: ($0 < c < b < 1$). The payoff matrix for 2-player interactions, from the point of view of a player, is

$$A = \begin{bmatrix} A_{CC} & A_{CNc} \\ A_{NcC} & A_{NcNc} \end{bmatrix} = \begin{bmatrix} b - \frac{c}{2} & b - c \\ b & 0 \end{bmatrix} \quad (4.3)$$

In the above payoff matrix, the strategies represented alongside the payoff parameters are defined as follows. The value of the matrix element A_{NcNc} expresses the fact that, if both nodes decide to play Nc, then no data is relayed and each player gets a payoff 0. The value of A_{CC} tells that if both individuals play C (and then they are interested to form collaboration in packet forwarding) each of them obtains an expected payoff ($b - \frac{c}{2}$). The off-diagonal elements tell that if a node decides to play C while another chooses to play Nc, then the latter succeeds in sending its data to the BS at no cost and gets a payoff b, while the former gets a payoff ($b - c$).

This matrix representation is well-defined as a 2x2 symmetric game. Indeed, it is clear that ECG is a symmetric game. Individuals have the same strategies correspondingly the same payoffs. They have an equal chance to contest for certain strategy and receive the same benefit as a result of contesting that strategy. The payoff that nodes received depends on the strategies of the individual nodes rather than the category we are considering for an examination. Thus, playing either C-strategy or Nc-strategy will be the best to try for every node.

Thus, when a C-node meets another C-node, which happens with probability x_C , it obtains a payoff $A_{CC} = (b - \frac{c}{2})$, whereas if it meets a Nc-node, which happens with probability x_{Nc} , it obtains $A_{CNc} = (b - c)$. The expected value is the following utility:

$$U_C(x_C) = (1 - x_C)(b - c) + x_C(b - \frac{c}{2})$$

Similarly, the expected payoff for a Nc-node is

$$U_{Nc}(x_C) = x_C b$$

Using the average payoff

$$U_{avg}(x) = x_C U_C(x) + x_{Nc} U_{Nc}(x)$$

the replicator dynamic equations can be developed as

$$\begin{aligned}
x_C' &= x_C(U_C(x_C) - U_{\text{avg}}(x_C)) \\
&= x_C(U_C(x_C) - x_C U_C(x_C) - x_{Nc} U_{Nc}(x_C)) \\
&= x_C((1 - x_C)U_C(x_C) - x_{Nc} U_{Nc}(x_C)) \\
&= x_C(1 - x_C)(U_C(x_C) - U_{Nc}(x_C))
\end{aligned} \tag{4.4}$$

This first derivative vanishes at three points that we denote by $x_C^{(0)}$, $x_C^{(1)}$ and $x_C^{(*)}$. The first two are trivially $x_C^{(0)}=0$ (no one plays C) and $x_C^{(1)}=1$ (everyone plays C); the reminder corresponds to

$$(U_C(x_C) - U_{Nc}(x_C)) = 0 \tag{4.5}$$

or, explicitly,

$$(1 - x_C)(b - c) - \frac{c}{2}x_C = 0 \tag{4.6}$$

which yields

$$x_C^{(*)} = \frac{2(b - c)}{2b - c} \tag{4.7}$$

The stability analysis can be performed by differentiating Equation 4.4 to get the second derivative x_C'' : a positive value of this derivative corresponds to stable points. Substituting each of the three points, one can check that $x_C^{(0)}$ and $x_C^{(1)}$ are unstable equilibrium points. The point $x_C^{(*)}$, on the contrary, is the stable state where it is an ESS for this pair-wise game.

4.3.3 Multi-players Contest Game

Now we lift the number of nodes that we have earlier discussed. Let us consider the population of large numbers of individual nodes that meet one another. Again assume that individuals adjust their strategies in line with the benefit they acquired in the population of nodes.

With this regard, we compute the MCG in two scenarios: global population dynamics and group-wise interaction of nodes. The global population dynamics corresponds to studying the problem within a population of the whole nodes interaction (where any node player is assumed to interact with the same probability with any other nodes in the large population). This concept has been considered, in the next section, to study the behaviors of multiple nodes interactions. On the other hand, the group-wise interaction corresponds to a finite number of players (i.e.,

nodes) in the neighbors. This analysis is refined from the former by taking into account that, in practice, the collocated nodes interact with a small set of neighbors by limiting their transmission range. Hence, they form a cluster in the region of their interactions. For this purpose, an evolutionary cluster-game is considered and its analysis will be presented in Chapter Five. It is slightly a more accurate (though still approximate) model in representing the characteristics of nodes.

4.4 The Analytic Model of Dynamic System

In this section, the population of nodes' interaction is studied. An evolutionary dynamics is considered for this population by using replicator systems and its behaviors are also evaluated.

In connection to this, a rewarding mechanism that has been integrated into the model for better improvement of collaboration (i.e., increasing the number of mutual collaborative nodes) has been discussed.

A) Global Population of Node Interactions

According to the current modeling, the whole non-collaborative nodes interact randomly in the population dynamics. It is assumed that these nodes maximize their respective transmission ranges to act together. In this type of games, the incentive of all players would be expressed by a global utility function that would help the nodes to converge firmly. For instance, the classical GTs of such global interaction of nodes are studied in [142], [163] for the purpose of designing the topology of sensor networks.

Individual node shares information about this evolutionary game in which it calculates the received benefits in line with the strategy it currently played in order to update its next round strategies. This considers the behavior of large populations of non-collaborative nodes that repeatedly engage in anonymous ways. Here, we assume that a system consists of well-mixed N nodes population; a node competes with a group of other $N - 1$ nodes. Concerning this issue, each node's interaction outcome depends not only on its particular choice but also on the other nodes' choices. The payoff of a node depends on the strategy of the node itself and the strategies of other $N - 1$ competing nodes.

Now let us consider the ECG model. The C-node is a collaborative node, i.e., willing to forward the other nodes' packets, in addition to its own. Thus, the payoff of C-node is defined

as follows. If the node under consideration is the sole C-node, then its payoff is $(b - c)$. If there are two C-nodes then each of them gets a payoff $(b - \frac{c}{2})$. Where there are n numbers of C-nodes in the N nodes population, an individual C-node has a payoff of:

$$A_c = b - \frac{c}{n}, \quad \text{where } n \in \{1, \dots, N\} \quad (4.8)$$

The payoff of N_c -nodes also depends on whether a C-node is present or not. If at least one node, say node t , plays C-strategy, then the payoff of all other nodes will be b , except node t whose benefit b will be reduced by the cost of c . When there is no C-strategy then the payoff becomes 0 since the network has all N_c -strategy nodes that no one is willing to form collaboration. In such cases, nodes should send the packets to the BS by themselves; otherwise, their packets would be dropped by others. In many cases, these might be infeasible for resource-constrained nodes in terms of communication resources.

A N_c -node has a payoff of:

$$A_{N_c} = \begin{cases} 0, & n = 0 \\ b, & n \in \{1, \dots, N-1\} \end{cases} \quad (4.9)$$

In the evolutionary game, a large population should be studied using replicator dynamics: as a mechanism for selecting a strategy that provides the best fitness. Then, this strategy will be replicated in the nodes' population-wide where it is adopted by every node. As such, the context in the ECG model has been designed in order to adjust the strategy and the relative shares of different nodes. The portion of individuals that play certain strategy would be adjusted with respect to the relative advantages they received. Accordingly, entire nodes amend their strategic behaviors toward a public advantage.

Let us consider once again, our previously derived Equation 4.1. The idea behind this equation is articulated as follows. The number of nodes that use s_i strategy will increase if the strategy s_i brings a maximum payoff to them than the average level. The growth rate of such nodes will be represented in proportion as $\frac{x_{si}'}{x_{si}}$. It is the difference between strategy x_{si} 's current payoff and the current average payoff in the entire nodes population.

Similarly, we can express, a probability that one node plays a pure strategy s_i as $x_{si}(t)$, thus, for this node $x(t)$ can be equivalently expressed as a mixed strategy. A strategy s_i will be adopted

by sensor nodes more frequently if a pure strategy s_i brings a higher payoff than the mixed strategy. That means $x_{si}(t)$ (the probability of taking s_i strategy) will increase among the population. The rate of this probability will be represented as x_{si}' . Thus, x_{si}' is proportional to the difference between strategy s_i 's payoff and the one achieved by mixed strategy.

Therefore, considering the interactions of the whole nodes as a population, one can revise the ECG that was defined in Section 4.3.2. In this case, a large number of nodes are considered in which they are approximately well-mixed in the homogeneous population. These individuals are randomly matched to play a population game where they adjust their pure strategies from a given set, $S = \{C, Nc\}$. This is the case because the received payoff depends only on the strategies they played; not on who is playing against them.

Thus, the previously derived replicator dynamic equation can be rewritten in the particular context of strategic development.

$$x_C' = x_C[U_C(x) - U_{avg}(x)] \quad (4.10)$$

The strategic playing of node population is assumed to be infinite (such as sampling with replacement), in which the strategy should be sampled and grouped into an unlimited number of times with other possible strategies. This leads to the binomial distribution of nodes grouped composition. As such, from a large number of node interactions, the strategy of certain sub-population nodes is randomly chosen for a consideration. The payoff (or fitness) of this chosen strategy is time-dependent; let us assume that $x_C(t)$ is the probability of selecting a C-node, and $(1 - x_C(t))$ is the probability of selecting Nc-node at time t . By considering one C-node that interacts with other $N - 1$ nodes, this C-node may pick additional k C-nodes; the remaining population will be $(N - k - 1)$ Nc-nodes to form a total of N -nodes packet forwarding. Then, according to the binomial distribution, over all the possible ways of forming such groups can be computed by averaging on them, such population interaction was studied in [120], [121], [123]: by taking into account the various strategic combinations of other $N - 1$ nodes within a certain time interval.

Let us assume that $U_C(x_C)$ - is an average payoff for C-nodes and $U_{Nc}(x_C)$ - is an average payoff for Nc-nodes. So, if x_C is the given probability of selecting $(k + 1)$ C-nodes from the group of N -nodes population: as such, one can compute $U_C(x_C)$ and $U_{Nc}(x_C)$.

Thus, $U_C(x_C)$ can be

$$U_C(x_C) = \sum_{k=0}^{N-1} \binom{N-1}{k} x_C^k (1-x_C)^{N-1-k} A_C(k+1) \quad (4.11)$$

Similarly, $U_{Nc}(x_C)$ can be given by

$$U_{Nc}(x_C) = \sum_{k=0}^{N-1} \binom{N-1}{k} x_C^k (1-x_C)^{N-1-k} A_{Nc}(k) \quad (4.12)$$

Hence, as evolution proceeds in ECG, the number of C-nodes and Nc-nodes becomes time-dependent. Therefore, one can easily notice from an Equation 4.10 in order to study how these happened. For instance, if the average payoff of $U_C(x)$ is greater than $U_{avg}(x)$ (average payoff of the whole nodes population), the proportion of C-nodes in the population will be increasing. Otherwise, C-strategy nodes will be decreasing, since $U_C(x)$ shall be less than $U_{avg}(x)$. Thus, $U_{avg}(x)$ can be defined as:

$$U_{avg}(x) = x_C U_C(x) + (1-x_C) U_{Nc}(x) \quad (4.13)$$

Now we have all the elements, starting from the standard evolutionary dynamics of Equation 4.1, to write the replicator equation x_C' .

$$x_C' = x_C(1-x_C)(U_C(x_C) - U_{Nc}(x_C)) \quad (4.14)$$

This equation can be used as a mechanism for determining an equilibrium state in the large population. Thus, considering the first derivative, Equation 4.14 has three equilibriums. Two trivial ones with $x_C^{(0)}$ and $x_C^{(1)}$, and a non-trivial equilibrium ($x_C^{(*)}$). Both $x_C^{(0)}$ (nobody plays C) and $x_C^{(1)}$ (everyone plays C) are trivial equilibriums that they are unstable.

After the strategies transient, the system evolves into stable equilibrium, i.e., ESS, in which no node will deviate from playing an optimal strategy (i.e., staying in this state is the perspective of node to receive a better benefit). When $x_C \in (0,1)$, the solution of $(U_C(x_C) - U_{Nc}(x_C) = 0)$ is the only stable equilibrium. It indicates that the dynamic system approaches to an ESS where C-nodes and Nc-nodes co-exist, regardless of the strategy they initially adopted.

$$U_C(x_C) - U_{Nc}(x_C) = 0 \quad (4.15)$$

Equation 4.15 designates that the achieved system approaches to a stable state. C-nodes and Nc-nodes are complimented in the population by this dynamic system, in which the ratio of

their existence depends on the payoff matrix. In this consideration, providing an incentive will be expected to increase the ration of C-nodes (collaborators). Further, it is important for both C-nodes and Nc-nodes to balance their communication resources.

B) Incentive-Based Collaborative Equilibriums

Here, an incentive (also called a reward) is incorporated into the payoff that we have defined earlier in order to enhance and adjust the number of C-nodes in the population.

Replicator dynamics of cooperative enhancement is studied in [123] through improving the works of [120], [121]. Therefore, along these works, we analyze the mutual operation of nodes: the presence of rewarding improves the payoff functions in the process of their interaction. As a consequence, the attitude that nodes have for cooperation can be changed, i.e., the response to set up the collaboration will be enriched. As a result, the total energy consumed per round by each individual node to forward the packets has highly improved. This will bring additional advantages to all nodes both for C-nodes and Nc-nodes since their packets reach the BS with minimum energy consumption.

This implies that packets communication would be efficient if more C-nodes are there to share the task which has been validated by simulation results. Given a reward r and the number of C-nodes n , this mechanism is defined as

$$r \left(1 - \frac{1}{n} \right).$$

A reward is coupled with a minimum energy (i.e., longer network lifetime) operations needed to forward packets. This mechanism increases and balances the number of collaborative nodes that are expected to exist for large nodes' population that randomly interact.

Such benefits will be determined by the number of C-nodes. If there is a single C-node under consideration (let $n = 1$) in the intended network area, then it has $(b - c)$ payoff. In this case, no additional rewarding is provided as the C-node in the sensor population is solely one (i.e., $r \left(1 - \frac{1}{n} \right) = 0$, this is also true according to the rewarding mechanism). If there are two C-nodes, the task of forwarding the packets to the BS is shared among the two nodes; as a result, their payoff has increased, and each of them receives $\left(b - \frac{c}{2} \right) + r \left(1 - \frac{1}{2} \right)$ payoff, (i.e., energy utilized by each node is reduced). In general, if n C-nodes have established collaborations to

forward packets in the field of N nodes population including the node itself, the payoff of C -nodes becomes: $\left(b - \frac{c}{n}\right) + r\left(1 - \frac{1}{n}\right)$.

The payoff of n C -nodes can be

$$A_C = b - \frac{c}{n} + r\left(1 - \frac{1}{n}\right) = (b + r) - \frac{c + r}{n}, \quad n \in \{1, \dots, N\} \quad (4.16)$$

Moreover, the N_C -nodes also received the advantages from the presence of more C -nodes. The more C -nodes are available to share the task of forwarding, the less energy consumption, thereby, extending network lifetime. Thus, the N_C -nodes are benefited, i.e., they get additional payoffs. Accordingly, if there are n numbers of C -nodes in the network, the payoff of N_C -node becomes, $b + r\left(1 - \frac{1}{n}\right)$. When there is no C -node, their payoff becomes 0 since all nodes have played N_C strategies. No one is willing to perform the task of collaboration: each node should try to forward only its packets to the BS, which might consume much communication energy.

So, the N_C -nodes have the following payoff:

$$A_{N_C} = \begin{cases} 0, & n = 0 \\ b + r\left(1 - \frac{1}{n}\right) = (b + r) - \frac{r}{n}, & n \in \{1, \dots, N-1\} \end{cases} \quad (4.17)$$

Therefore, this incentive mechanism is integrated into our model in computing the mutual collaborative equilibrium. Consequently, simply by substituting Equation 4.16 and 4.17 into Equation 4.11 and 4.12, respectively gives $U_C(x_C)$ and $U_{N_C}(x_C)$, in terms of N , b , c , and r .

$$U_C(x_C) = \sum_{k=0}^{N-1} \binom{N-1}{k} x_C^k (1-x_C)^{N-1-k} (b + r) - \frac{c + r}{k + 1}$$

$$U_{N_C}(x_C) = \sum_{k=0}^{N-1} \binom{N-1}{k} x_C^k (1-x_C)^{N-1-k} (b + r) - \frac{r}{k}$$

Thus, $U_{avg}(x)$ will be required to be redefined: $U_{avg}(x) = x_C U_C(x) + (1-x_C) U_{N_C}(x)$ when rewarding r is introduced: as such, replicator dynamics x_C' can be rewrite as

$$x_C' = x_C(1-x_C)(U_C(x_C) - U_{N_C}(x_C)).$$

Formerly x_C' has been computed, in the same manner: $x_C^{(0)}$, $x_C^{(1)}$ and $x_C^{(*)}$. The first two equilibriums are unstable strategy; either N_C or C dominates the population. However, the latter

is stable, i.e., an internal equilibrium when the population of both strategies coexists. Thus, for $x_C \in (0,1)$, by introducing parameter r , we compute ($U_C(x_C) - U_{Nc}(x_C) = 0$). It is also an ESS.

Therefore, one can work out this equation at the stable state to get a collaborative equilibrium $x_C^{(*)}$ by using payoff parameters (i.e., benefit, cost, and reward) and a number of N nodes.

Therefore, the N^{th} order of $x_C^{(*)}$ equation is represented as:

$$(b - c) + \sum_{n=1}^{N-1} \binom{N-1}{n} \left(\frac{x_C^*}{1 - x_C^*} \right)^n \left(\frac{r}{n} - \frac{c + r}{n + 1} \right) = 0 \quad (4.18)$$

Since the behavior of node depends not on the absolute values of benefits, costs, and rewards, but on their relative value, $x_C^{(*)}$ is computed using their relations: cost-to-benefit ratio ($\frac{c}{b}$) and reward-to-benefit ratio ($\frac{r}{b}$).

Assume that ($\frac{c}{b} = w$) and ($\frac{r}{b} = d$), thus, we can rewrite the above equation in simplified form:

$$w = \frac{1 + d \sum_{n=1}^{N-1} \binom{N-1}{n} \left(\frac{x_C^*}{1 - x_C^*} \right)^n \frac{1}{n(n+1)}}{1 + d \sum_{n=1}^{N-1} \binom{N-1}{n} \left(\frac{x_C^*}{1 - x_C^*} \right)^n \frac{1}{(n+1)}} \quad (4.19)$$

For a small number of nodes, this equation can be solved analytically while it can be solved numerically for an arbitrarily large number of nodes. Regarding to Equation 4.19, its $x_C^{(*)}$ is evaluated and discussed in the following numerical simulations.

Figure 4.1 shows the evolved equilibrium distributions of nodes, for $N = 6$, and d ($d = 0.01, 0.3, 0.6, 0.8$), and the values of w is in $[0,1]$. The results show that the equilibrium probability of collaborative nodes decreases with increasing the values of w , with more rapidly dropping for smaller values of d under the same number of nodes. On the other hand, the nodes achieve larger collaborative equilibrium for a larger value of d . The inequality ($\frac{r}{(N-1)} - \frac{(c-r)}{N} > 0$) is used to evaluate the condition of having all nodes in collaborative condition (AllC-node states) for any given $x_C^{(*)}$. The collaborative equilibrium condition that all nodes evolve into AllC-nodes (i.e., $U_C(x_C) - U_{Nc}(x_C) > 0$) is stable fixed point for $x_C^{(*)} = 1$, or an unstable fixed point for $x_C^{(*)} < 1$. To get AllC-nodes, if d and w are given the inequality $N < 1 + \frac{r}{c}$ holds; otherwise,

the inequality $(N - 1)c < r$ holds when the parameters N and c are given. For instance, the behavior of AllC-nodes are given for $N = 6$, $w = 0.1$ and $d = 0.8$.

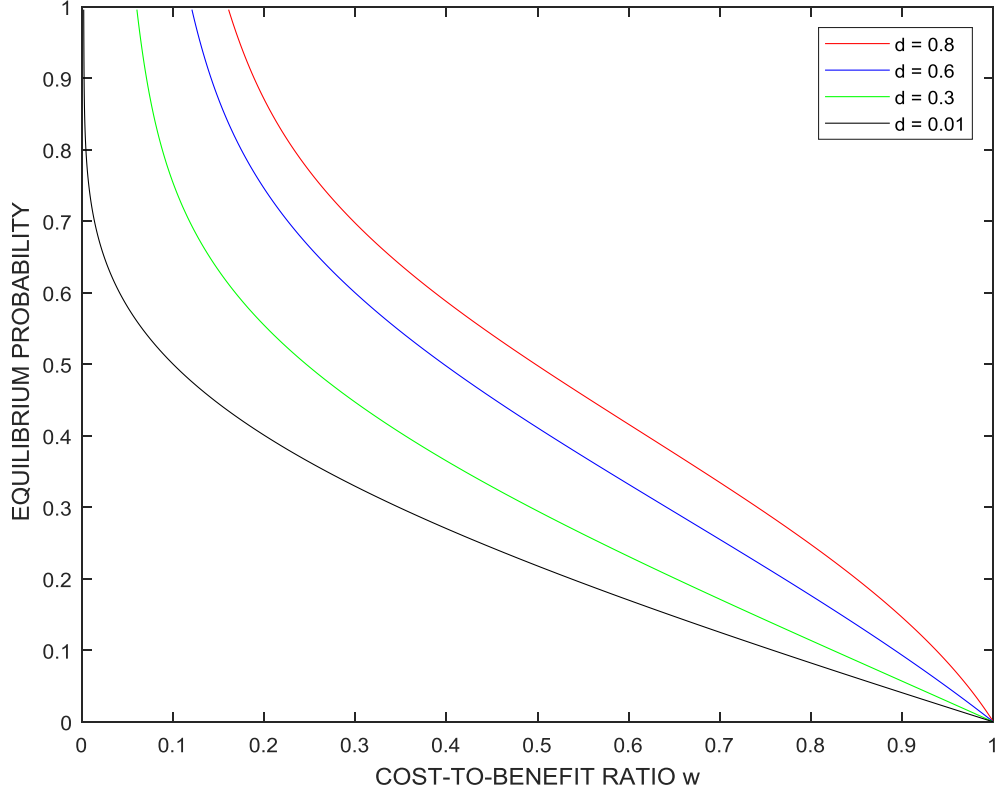


Figure 4.1: The Equilibrium Probability of Collaborative Nodes ($N = 6$) versus w ; when the Value of d varies

The equilibrium system of collaborative nodes with respect to different values of w , as the value of $d = 0.6$ is shown in Figure 4.2. The number of sensor nodes are also different ($N = 4$, $N = 10$, $N = 20$, $N = 30$). The probability of the collaborative equilibrium will be decreasing as the parameters of w increases, with a more rapidly dropping down for a large number of nodes, by considering the same value of d . This is due to the fact that in the presence of a large number of nodes with a larger value of w , more nodes will be motivated to join non-collaborators to save their communication resources. This means that they simply tend to wait for some other sensors to perform the task of forwarding packets on their behalf. On the other hand, the equilibrium probability increases when N and w are smaller.

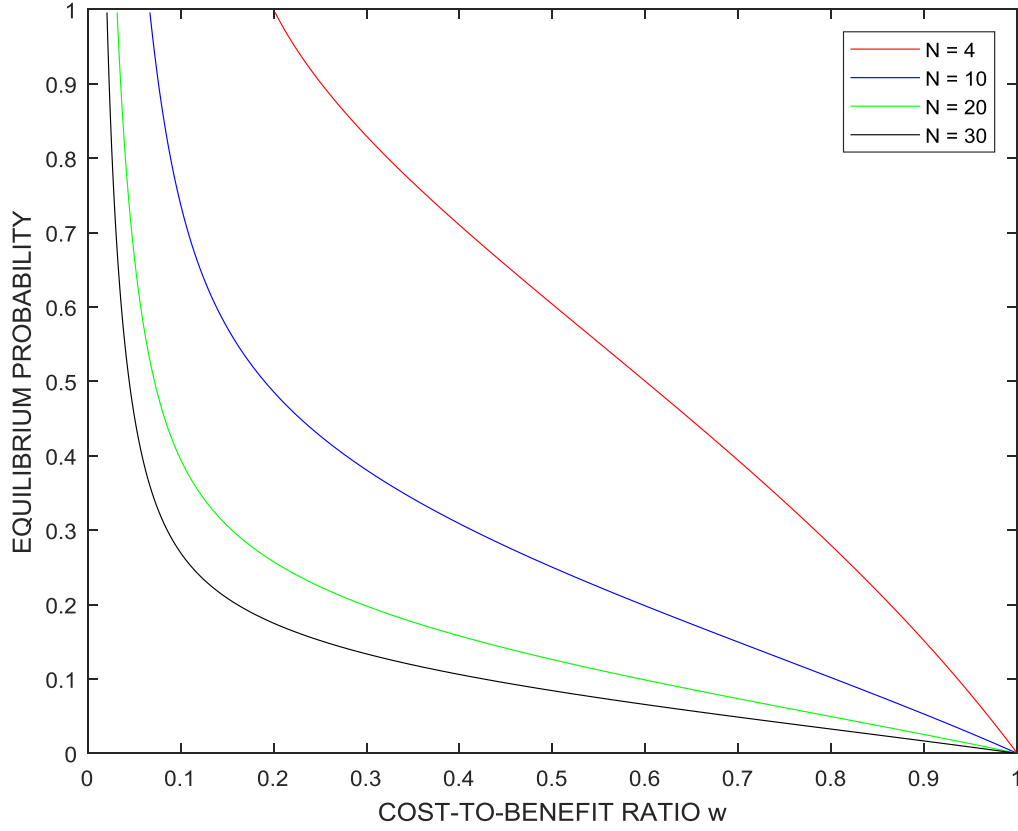


Figure 4.2: The Equilibrium Probability of Collaborative Nodes ($N = 4, N = 10, N = 20, N = 30$) versus w ; when $d = 0.6$

The effect of collaborative nodes equilibrium when the number of nodes increases ($N = 50$) for $w = 0.1$ and $d = 0.8$ is shown in Figure 4.3. For $w = 0.1$ and $d = 0.8$, as it is shown on the graph, the points of $(U_C(x_C) - U_{N_C}(x_C) > 0)$ and $(U_C(x_C) - U_{N_C}(x_C) < 0)$ are said to be stable and unstable AllC-node states respectively. For example, since $N < 1 + \frac{c}{r}$, for all values of x and $N < 9$, the system will attain an AllC-nodes (stable fixed point). Since $N > 1 + \frac{c}{r}$, for the large size of sensors $N > 9$, the system reaches an unstable fixed point. The point on the graph where collaborative equilibrium meets at stable state is called a fixed point (for instance the point where, $N = 15$ and $x_C^{(*)} = 0.6305$).

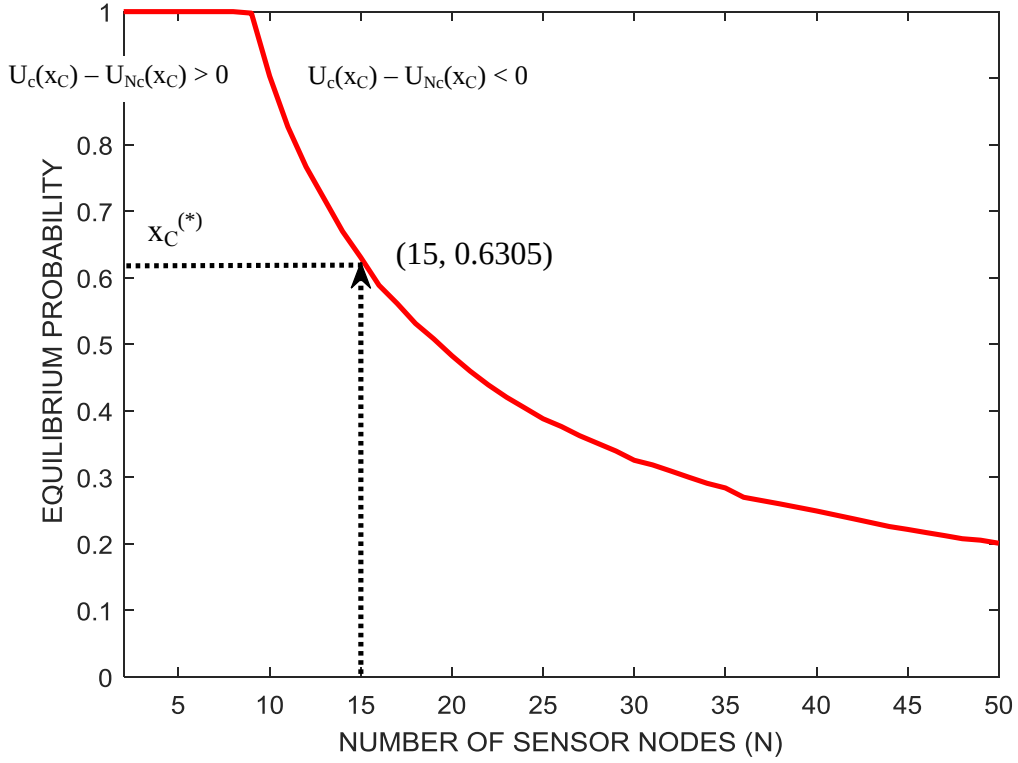


Figure 4.3: The Effect of Number of Sensor Nodes ($N = 50$) on Collaborative Equilibrium, for the Parameter $d = 0.8$ and $w = 0.1$

In a nutshell, we have shown the global asymptotic stability of equilibrium (i.e., a cooperative probability adjustment of nodes). We have also indicated that the stable equilibrium depends on the number of nodes in addition to the relation of payoff parameters. The interactions of these N -nodes oscillate around the equilibrium. Additionally, at the time of nodes' strategy updating, if there are enough number of C-nodes, to get a better payoff the strategy of certain nodes will be forced to change into Nc-strategy as of the inequality $(n - 1)c > r$.

Once collaborative equilibrium has been achieved, it keeps the co-existence of C-strategy and Nc-strategy in the evolution. If there are n C-nodes in the N -nodes, based on Equation 4.16, the payoff A_C of each C-strategy node is computed. If one of the C-nodes changes its strategy into the Nc-strategy, the payoff A_{Nc} is computed using Equation 4.17 and for this node, the payoff condition becomes $A_{Nc} > A_C$ which is also true that $(n - 1)c > r$. For a given fraction of C-nodes, more C-nodes are expected in the network, as a result, to bring a lower $x_C^{(*)}$, the larger C-nodes have also a tendency to promote the Nc-strategy nodes. In this manner, an ending

time of this evolutionary dynamics is indefinite since the ending time of sending messages is unknown to any of the nodes in advance. A node stops sending messages only when it has completely exhausted its energy.

4.5 Cluster-Based CPF Algorithm

In this section, the first packet forwarding algorithm has been proposed by taking into account the strategies of individual nodes. When the global interactions of nodes achieved the equilibrium probability, the collaborative forwarding would be maintained. This is a circumstance where the achieved equilibrium guides the nodes' behaviors in adopting a common strategy (i.e., all nodes realized the benefit obtained). Then, the preliminary investigation of CPF algorithm is evaluated in comparison with the NcPF default case.

Our CPF algorithm works within the specific phase of the cluster-based algorithm. As such, it has been designed to determine a potential Forwarder-Head (FH) node. FH determination sub-phase has proposed in accordance with the achieved collaborative equilibrium between non-cooperative nodes, as such, cluster formation will be followed. It is clear that initially non-cooperative nodes adopt several behaviors during these phases in order to skip oneself from FH selection. For the remaining life-cycles of CPF algorithm, we have adopted the standard assumptions. Recently, such assumptions have been very common in cluster-based routing algorithm design.

4.5.1 State of FH-Determinations

This algorithm is intended to evaluate our analytic model with more realistic assumptions. The clustering topology has also been provided in order to assess the scenario in representative applications. Thus, CPF algorithm is proposed according to the concepts of the asymptotic stable state of nodes. Although the models used classical GT approaches, such an assumption was made by previously designed algorithms: CROSS [14] and CORE [16]. In both of these routing algorithms, the rationalities of selfish nodes have been assumed during nodes' global interactions that reach static NEs. However, in our case, the model is notably different as it has been considered the evolutionary dynamics of nodes. The numerical analytic model of our dynamic state has discussed in Sections 4.3 and 4.4. A cooperative stable equilibrium between such nodes has also been confirmed by using analytical and numerical solution.

In our evolutionary game, nodes decide the strategy by which they whether cooperate or not. So, the participant nodes analyze the resource benefits to adjust their dynamic strategy in every interaction. As such, they reach to the equilibrium strategy which is expected to be adopted by each node. This equilibrium guides nodes toward performing a better way to maximize their resource utilization. Owing to this, individual nodes agree to play C-strategy equilibrium; nevertheless, if anyone disobeys this agreement, its resources will be depleted. Hence, as far as the equilibrium is maintained, every node has to abide by it. As such, sensor node recalls this state in the course of FH selection. Hereafter, we called this node as a collaborative node.

In CPF algorithm, the node prefers to forward its packets through another collaborative node to save its communication resources. As a result, the entire nodes have to announce their existence during the early stage of deployment. Therefore, broadcasting information is expected from those nodes that are interested in participating in this algorithm. By getting this information from each other, the nodes in the collocated network recognize one another. If a node does not announce itself, it will be unable to pass its packets through the others, which means that this node has to try by itself. Nevertheless, every node drops the data packets of the other nodes that it did not recognize.

The global collaborative equilibrium $x_C^{(*)}$ and cooperative-rate of each node have been considered in the course of FH determination. Collaborative nodes share probability $x_C^{(*)}$ in the networks. The value of cooperative-rate gets updated at every round for node that is not currently the member of FH list (S_c). Such an update will be made in accordance with individual node's cooperative history. S_c is assumed as a set that contains the list of FH nodes (also called CHs). Initially, S_c is empty set since no node has served as CH. In addition, S_c will be updated by adding the node that has currently been on the FH in the due process.

Nodes that have cooperative-rate greater than zero need to broadcast their respective cooperative-rate information. It is assumed that such nodes participate inside their respective communication ranges within their neighboring nodes to determine a potential FH. In that context, the value of their cooperative-rate is evaluated. The one that has a maximum cooperative-rate gets granted the permission if more than two nodes have announced themselves in the same range. Otherwise, the broadcasted node will be granted to be FH in the current round since it is the only one to be available. In due course, granted FH node sets its FH to one and be

added to S_c . Later, this node has to broadcast the advertisement message while all the other nodes are returning to the normal state after they heard such message.

Then, the process of cluster formation will be followed. Accordingly, the nodes that have the FH equal to one will broadcast their announcement, whereas the other nodes that hear this announcement will also request to join. In addition, the latter nodes update their state of forwarder-member to one. On the other hand, the node might receive an advertisement message from more than two FHs. In this regard, such a node chooses to join a FH that has a maximum cooperative-rate by evaluating their cooperative-rates. Then, the CH also allocates the time schedule for its member nodes, i.e., for those nodes by requesting to join it. The current CH creates a TDMA based time slot schedule and broadcasts to all of its cluster members. Thus, by dividing the signal into different time slots the TDMA allows several member nodes to share the same frequency channel in order to communicate with the CH.

Eventually, the node proceeds to the packet forwarding when either its forwarder-head or its forwarder-member becomes one. During this time, every member node senses the data in its surrounding and sends that to its CH, according to the assigned time slot. As the packet forwarder leaders, the current CH collects the packets from its member nodes and performs packets aggregation and also forwards the result to the BS. In our assumption, the BS is being located at a center and FH reaches the intended destination in one-hop.

Sometimes, there is a node that cannot hear any of the FH announcements; still, for such a node, its respective forwarder-member has been zero. Such things are likely happening when nodes might not be satisfied with the achievement of the present equilibrium. Thus, considering the application either it waits for some time to bring up a better equilibrium probability in which this node has to play C, or it switches into a direct transmission. As of a current implementation, we allowed nodes to evaluate their cooperative-rate information once again in order to contest for FH; otherwise, node considered itself as the only one in that area to send its packet directly.

Sensor node that has been served as FH in the current round is exempted in the next round until all other nodes will possibly take the role. The FH status of such node returns back into zero. In the due course, it has to stay in the S_c set to preserve its resource. At the end of every round, the other nodes also return their membership status into zero (i.e., forwarder-member sets to zero). In addition, S_c is also reorganized (reset to empty) when all-alive nodes have been served as FH

currently. From this angle, the algorithm starts a fresh round in which every collaborative node is expected to contest. FH selection state diagram of CPF algorithm is shown in Figure 4.4 below. Accordingly, it will be repeated several times, as such, it has been expected to end when an energy resource of the whole nodes have got depleted.

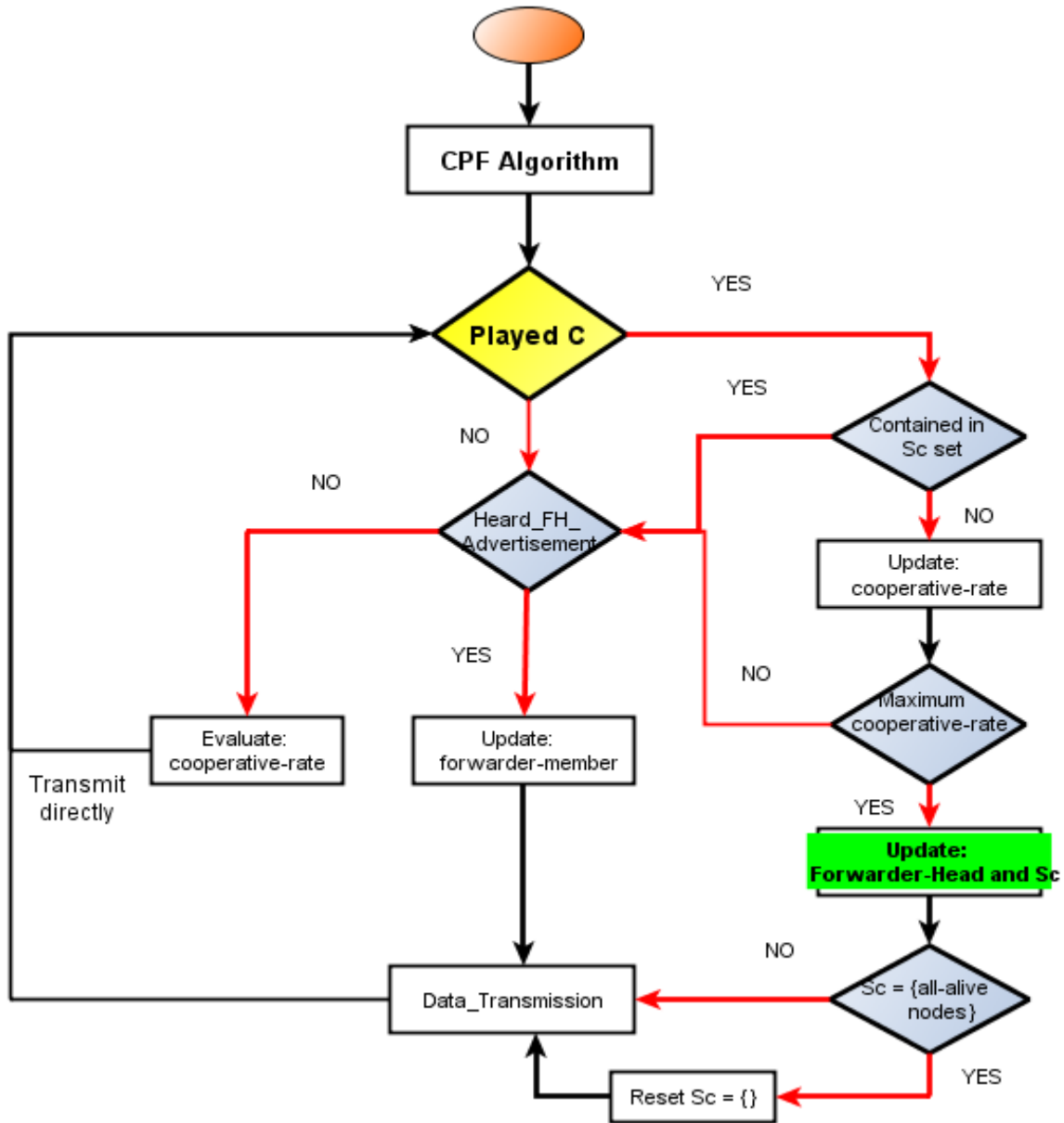


Figure 4.4: FH-Determination State Diagram for Cluster-based CPF Algorithm

4.5.2 The Default NcPF Algorithm

A mechanism of default packet forwarding is introduced in this section, where an inability of nodes' cooperation is realized in this discussion. In this scenario, materializing collaboration with other nodes is not the interest of such nodes. Accordingly, we studied the behaviors they implement in cluster-based routing algorithm and their effect on the network performances. It can be adopted according to the procedure followed in [17], [21]. For instance, the solution that proposed in [17] was compared with the default case when non-cooperative nodes were directly transmitting the packets to the destination, whereas the proposed algorithm in [21] was compared along with the hierarchical routing (LEACH-C [6]) when nodes were being selfish. In addition, in [25], the performance degradation of clustering algorithm was studied when selfish nodes got dropped the other nodes' packets. Our development context is remarkably different from those cases. Accordingly, in our case, the default NcPF algorithm has been proposed in line with comparing to cluster-based CPF algorithm (see Figure 4.4). The NcPF clustering has been considered at non-collaborative behaviors of a node. In this algorithm, there is no collaborative equilibrium that emerges between nodes. Rather we assumed in the design the case where nodes misbehave with their neighbors in the course of packets communications. Misbehaving nodes might not be interested to announce their existence in the process of placement as well. Thus, they might not be recognized by other normal nodes in their nearby communication field.

In this regard, the behavior of selfish nodes was assumed to be a free rider in the NcPF algorithmic development. Interestingly, it is not its concern to participate in the process of FH-determination as well. As such, it might not be interested in announcing itself as FH, since taking that role consumes its resources. As a chance, if it suddenly recognized by its neighbors, this misbehaving node could not be concerned in allocating the TDMA schedule for its neighboring request. Therefore, such neighboring nodes might follow a random time slot to send their own packets to their nearby recognized node, in which case, the coming packets from different nodes might collide. Otherwise, simply, such a selfish node prefers to receive and drops some packets, instead of aggregating and forwarding the similar one.

On the other hand, if the selected FH is a cooperative node, it will forward the packets of every node including that of a selfish one. Provided that the considered node is selfish, a direct

communication or another nearest cooperative CH's resource is utilized egotistically while sending only its own packets. In this case, the BS is likely to receive duplicated packets from several selfish nodes located in the same area of deployment. As a result, more energy has consumed and also the network bandwidth is overwhelmed by such communications of nodes.

Lastly, a preliminary investigation has been conducted to analyze the performance achievement of cluster-based CPF algorithm. Accordingly, the network performances for both CPF and NcPF algorithms have been quantified with respect to the nodes' remaining energy and the subject of payoff parameters. Thus, for this purpose, we have taken the random values ($w = 0.1, 0.5, 0.8$) and ($d = 0.5, 0.7, 0.9$) as a representative test cases. The remaining parameters of the experiment are shown in Table 6.1.

It has been observed that the performance evaluation metrics of NcPF algorithm have no relation with the payoff parameters. Since during their deployment, nodes have preferred to initially adopt selfishness, they remained into that behavior in the course of routing as well. In this regard, evaluating the proportion of payoff is not required; this has been confirmed in the simulation.

Corresponding to the number of rounds, the distributions of nodes having a positive residual energy are shown in Figures (4.5a, 4.5b, and 4.5c). A non-collaborative node lacks an agreement in NcPF to reach cooperation on the common goal. As such, since majorities of nodes are adopting selfishness, the network performance is poorly utilized. However, nodes conserve their energy in CPF algorithm due to the existence of a stable equilibrium that happens between them. Thus, nodes are motivated toward forming a collaboration with other nodes (i.e., updating their communicative strategies) in order to receive a better payoff. So, the energy dissipated per round by each individual node could dramatically be improved. This shows that the individual node collaboration refines greatly the communication performance of multiple sensor networks.

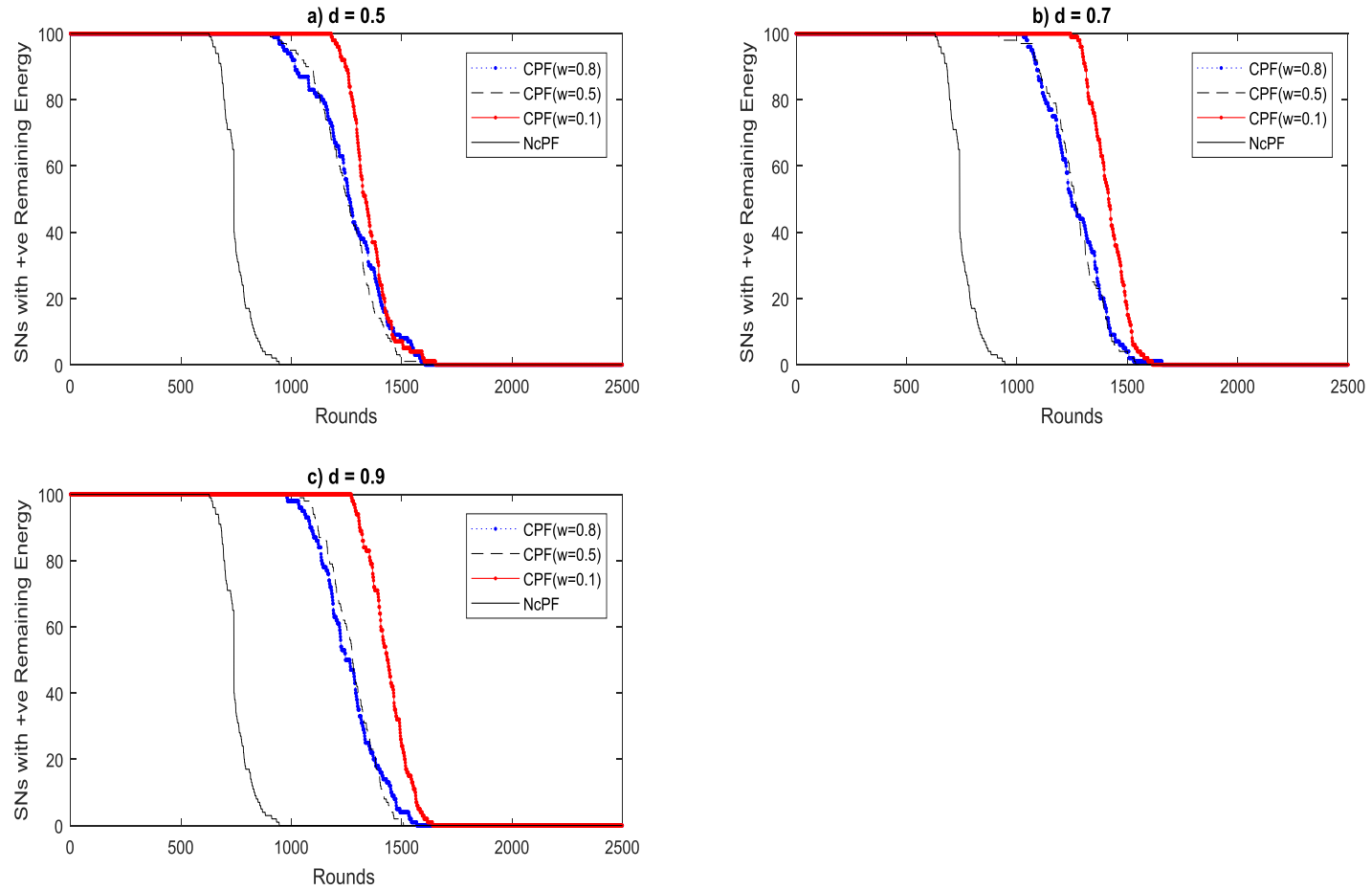


Figure 4.5: The Number of Sensor Nodes with Positive Residual Energy for CPF and NcPF Algorithms with Respect to Different Payoff Functions: a) Payoff Parameters, $d = 0.5$ and w (0.8, 0.5, 0.1); b) Payoff Parameters, $d = 0.7$ and w (0.8, 0.5, 0.1); c) Payoff Parameters, $d = 0.9$ and w (0.8, 0.5, 0.1)

4.6 Summary

In this chapter, the first study on the behaviors of nodes is conducted by using an EGT approach. Applying the theory of evolutionary dynamics over classical GT is given more attention due to fact that nodes are resources constrained. Such modeling concept can be applied in a real context in order to conserve the communication resources. An equilibrium existence in providing a better network service is investigated using both analytical and numerical analysis.

A distributed cluster-based CPF algorithm is proposed for nodes that established a global collaborative equilibrium. Its initial performance is assessed by comparing it with the default case of the NcPF algorithm. In CPF algorithm, all collaborator nodes interact locally so that they group themselves as a cluster in which node with a larger collaborative rate would be selected as a CH. Therefore, the member nodes communicate their packets to the BS through this CH. Contrarily in NcPF algorithm; nodes are not willing to collaborate with each other but are rather competing to exploit the other nodes' resources reducing nodes performance.

The analysis has been shown that the CPF algorithm extends the nodes energy utilization. This is due to the fact that nodes are interested in mutual collaboration by forwarding the packets to receive their optimal payoff. Such preliminary comparisons are promising for our research as suggesting the implementation of collaboration among nodes so as to improve the network performance.

Besides, by using extensive simulations, we have studied the effect of selfish nodes concentration on the performance of available clustering algorithm, (see in the Appendixes: Figures A.1 and A.2). According to the conducted assessments, the communication bandwidth has inefficiently been utilized which further increases data packets collision and interference as well as reduces network lifetime.

We have traced out that our CPF algorithm has still two limitations: (1) in reality, the resources constrained nodes cannot afford the issues to reach the nodes' whole population through maximizing their communication coverage. Since the battery-powered nodes consume a lot of energy during their maximum coverage, their lifetime is affected. Accordingly, for certain deployment areas, it is impossible for nodes to interact with each other in large communication

ranges. (2) As nodes have limited memory storage, incorporating rewarding mechanism is still a challenging and sometimes even impossible to imagine for the tiny sensor nodes.

Hence, in the presence of non-collaborative nodes, the resource utilization of each node must further be improved. The designing process must be cognizant of the actual reality of nodes' resources such as memory storage must be taken into account in addition to the battery lifetime. In the current designing, therefore, to improve the performance of the network, each node's behavior must be determined against its interaction with a neighbor. Thus, the work should concentrate on localizing the ability of nodes interaction with respect to their behaviors in the population. Through locally sharing the information, sensors must enhance their own estimates in order to evaluate the position that is related to their opponents. So, these must be incorporated into the algorithm designing in order to fully address the consequence of selfishness. Nevertheless, achieving this sophisticated collaboration solution by controlling the action of individual selfish nodes at a local level is challenging. In the following chapter, we have tackled these issues and obtained promising results.

CHAPTER FIVE: GREET ALGORITHM

Our earlier proposed model will be refined in this chapter. Accordingly, the model is expected to be analyzed by using slightly more accurate about sensor nodes communication assumptions. It takes into account that, in practice, the play-actors (i.e., nodes) interact with a small set of neighboring nodes. For this purpose, we use finite many players' evolutionary game of nodes that are locally clustered. In this aspect, the behavior of nodes is managed at a local level where the certain best strategy is expected to spread. Thus, an evolutionary clustering concept is implemented in the development of our algorithm. It is a distributed algorithm where information about individual nodes is independently disseminated.

This chapter is organized as follows. Section 5.1 introduces the overview of GREET cluster-based algorithm. This is followed by the analytic model of an evolutionary cluster-game and its stable equilibrium which is presented in Section 5.2. The details of the designing GREET algorithm is elaborated in Section 5.3. Its performance assessment is also discussed in Section 5.4. Finally, the summary of the chapter is drawn in Section 5.5.

5.1 An Overview

In practice, the populations of nodes do not intercommunicate globally in multi-scale (very large) networks. Rather they interact in group-wise, with a restricted number of representative neighbors. As such, they are expected to form an evolutionary dynamics (whether to assume a C-strategy or not) in their clustering region. So, by locally analyzing the available information, a strategy that brings a payoff above the average will be disseminated.

In our current consideration, we have studied a clustering process - in which individuals interact and update their strategies inside randomly formed finite groups - as the improvement of the classical assumption of a well-mixed population. Thus, in this chapter, we have proposed a GREET algorithm in line with the achievement of local dynamic equilibriums. Individual nodes that are in a CH-enabled state should initiate the algorithm: here a group of nodes retrieve the information about their neighbors and analyze their strategic adjustment statistics. These individuals attain a joint equilibrium (the system that controls the strategies and relative

shares of nodes), in which some of the nodes announce themselves as candidate CHs. As such, these candidates should further participate for an actual CH; and then the one appointed has to broadcast its CH information. Lastly, the other nodes (non-CHs) that receive the message must join as a client for the purpose of transmitting their packets.

5.2 Analytic Model of Dynamic System: M-node Game

In the previous chapter, we presented the analytic model where nodes globally interact as a population, in order to frequently share a utility function (as such, CPF algorithm has been designed). Such an algorithm required the comprehensive information of networks which could be difficult in the realities of nodes' dispersion. This chapter presents the group-wise interaction of neighboring nodes since routing algorithms only desires the local information. The same assumptions were made previously in [82], [139] in order to design the topology of the WSNs. Accordingly, the interaction of the entire nodes would be scattered over the region of networks. So, the whole network is divided into an independent operation of small networks. Thus, each sub-network or cluster will have a representative sample of nodes' population.

In this context, a more accurate analytic game model will be defined in the local clustering in accordance with the characteristics of the sensor networks. Therefore, this is a collection of a number of autonomous evolutionary games, each of them involving only a finite number of M-nodes. In an M-node game, a node competes against the other $M - 1$ sensor nodes (the complement set), and its payoff is computed accordingly. The replication dynamics of such a game has been studied in [127], building on the works in [120], [121]. Here, in line with these works, our localized analytical model will be amended and its numerical results will be studied.

5.2.1 An Evolutionary Cluster-Game

In this section, a model of evolutionary cluster-game has been defined. This is adopted since a small set of neighboring nodes interact in reality of networking communication. Accordingly, each node needs to share its information with its neighbors so as to reach a common equilibrium at a cluster level.

To this effect, the model that defined previously in Section 4.2.2 should be improved as an evolutionary cluster-game (M-node game): where a finite number of nodes locally interact, group-wise communication, $M = \{1, 2, 3, \dots, m\}$. They are non-collaborative players that play

a cluster-game with their neighbors by broadcasting a simple GREETING_MSG message. Accordingly, the slightly modified strategy space, $S = \{s_C, s_{Nc}\} \equiv \{C, Nc\}$, corresponds to bidding for a candidate CH (C) and not to bidding for a candidate CH (Nc).

U also represents the same parameters as it has been defined earlier. This is the set of utilities that each node receives while participating in the clustering game. Similarly, at a given time, a node adopts either strategy C or strategy Nc. A C-node is a node that adopts C, whereas a Nc-node is the one adopts Nc.

From the point of view of the number of individual nodes that are controlled by agencies, in our model, we assume that each agency has only a single node. Thus, the node that participates in this cluster game has to analyze its own interactive strategy as well as the obtained benefit when compared to the average payoff. In such a framework, a strategy that performs better in optimizing the resource utilization will be circulated between individuals. The same concept has been provided in the analytic model as well as in simulation.

5.2.2 Analytic Equilibrium Dynamics

In this section, we address the problem of finding the equilibrium strategy of nodes and analyze how this strategy will evolve into the stable state. First, we analyze of the cluster game in two-players. Then, we consider the evolutionary cluster-game of a finite number of nodes.

We consider the game of two-node; assume that individual node plays inside its transmission range: therefore, the game is said to be evolutionary cluster-game (M-node, when $M = 2$). This means, in a given round, individual bids whether to play the strategy s_C or s_{Nc} , continuously by analyzing its respective payoff, similar to the one defined under Section 4.3.2. Thus, for locally contested game as well, payoff matrix and stable equilibrium is represented using Equation 4.3 and Equation 4.4 respectively.

In the proposed model, we considered that everyone else of a node which played Nc-strategy is much better to have chosen C and be the CH for the time, rather than to have chosen Nc-strategy. In the former case, its message reaches the BS, in the latter the node saves power, but it fails to accomplish its mission.

Let us assume that an evolutionary cluster-game is played by a group of individual nodes when they are large in numbers. As such, this game is repeatedly executed by a subgroup of nodes

since everybody is uncertain about its neighboring nodes' action and utility: percentage of nodes that play a confident pure strategy may change.

In a given round, if at least one node plays C, then all the nodes in that sensing region will get a benefit b , within them, the C-nodes will incur to a c cost. Since only one of the volunteering nodes is chosen at random as a candidate CH, that cost in average will be shared equally among the C-nodes: if there is only a C-node, its payoff is $(b - c)$; if there are two C-nodes in the same sensing region, then the payoff is $(b - \frac{c}{2})$ and so on. Let the number of C-nodes, in a cluster of M -node, be indicated by h , with $h \in \{0, 1, \dots, M\}$ and let us denote the payoff to a node playing strategy s_i in a cluster containing exactly h C-nodes by $A(s_i, h)$. Then,

$$A(C, h) = b - \frac{c}{h} \quad (5.1)$$

As to $A(Nc, h)$, if $h = 0$ the payoff to the node playing Nc is zero, but as soon as $h > 0$ one has $A(Nc, h) = b$. The overall payoff matrix $A^{(M)}$ (where the apex indicates the fact that the player set contains M players) is

$$\begin{aligned} A^{(M)} &= \begin{bmatrix} A(C, M) & \dots & A(C, h) & \dots & A(C, 1) & A(C, 0) \\ A(Nc, M) & \dots & A(Nc, h) & \dots & A(Nc, 1) & A(Nc, 0) \end{bmatrix} \\ &= \begin{bmatrix} b - \frac{c}{M} & \dots & b - \frac{c}{h} & \dots & b - c \\ b & \dots & b & \dots & b & 0 \end{bmatrix} \end{aligned} \quad (5.2)$$

The element $A(C, 0)$ does not apply: if one plays C there is at least a C-node. Notice, in passing, that the payoff matrix of Equation 4.3 is a special case for Equation 5.2: it corresponds to $A^{(M=2)}$.

Now we can compute the average payoffs $U_C^M(x_C)$ and $U_{Nc}^M(x_C)$ of each strategy (with the usual meaning of the apex M). Considering the former, if the strategy of a node is fixed to C, then the number k of other C-nodes in the subset of M nodes chosen at random from a population where the fraction of C-nodes is x_C , is a Binomial variable: such variable has a probability parameter $p = x_C$ and a multiplicity parameter $n = (M - 1)$.

The expected utility $U_C^M(x_C)$ of the C-node is obtained averaging over k

$$U_C^M(x_C) = \sum_{k=0}^n \binom{n}{k} x_C^k (1 - x_C)^{n-k} A(C, k+1)$$

$$= b - c \sum_{k=0}^n \binom{n}{k} x_C^k (1-x_C)^{n-k} \frac{1}{k+1} \quad (5.3)$$

As to $U_{Nc}^M(x_C)$ one has

$$\begin{aligned} U_{Nc}^M(x_C) &= \sum_{k=0}^n \binom{n}{k} x_C^k (1-x_C)^{n-k} A(Nc, k+1) \\ &= \sum_{k=1}^n \binom{n}{k} x_C^k (1-x_C)^{n-k} b \\ &= \sum_{k=0}^n \binom{n}{k} x_C^k (1-x_C)^{n-k} b - [b(1-x_C)^n] \\ &= b - [b(1-x_C)^n] = b [1 - (1-x_C)^n] \end{aligned} \quad (5.4)$$

The second last simplification comes from the normalization condition of the Binomial function. Thus, the average utility is $U_{avg}^M(x) = x_C U_C^M(x) + (1-x_C) U_{Nc}^M(x)$. Notice that for $M = 2$ the above average utilities equal the utilities of the game in the previous Section 4.3.2.

We have two competing strategies in the population similar to the one in Chapter Four; therefore, we can write an equation of the form

$$x_C' = x_C(1-x_C)(U_C^M(x_C) - U_{Nc}^M(x_C)) \quad (5.5)$$

Like the one expressed in Chapter Four, this equation has also three critical points. The solutions $x_C^{(0)}$ and $x_C^{(1)}$ are unstable points, where $x_C^{(*)}$ is the only one that corresponds to the stability - the second derivation that yields positive value.

$$(U_C^M(x_C) - U_{Nc}^M(x_C)) = 0 \quad (5.6)$$

Also in this case, by appropriate stability analysis [121] one can check that it is a stable equilibrium. Hence, it can be expanded as

$$bx_C - b + c \sum_{k=0}^n \binom{n}{k} x_C^k (1-x_C)^{n-k} \frac{1}{k+1} = 0 \quad (5.7)$$

Thus, for $M = 2$ (i.e., $n = 1$) it recovers the same solution that we have derived for Equation 4.7. Considering the parameter of $w = \frac{c}{b}$, we can re-write the above equation as

$$x_C - 1 + w \sum_{k=0}^n \binom{n}{k} x_C^k (1 - x_C)^{n-k} \frac{1}{k+1} = 0 \quad (5.8)$$

The solution $x_C^{(*, M)}$ to this equation (hereafter, for brevity $x_C^{(*)}$) can be worked out analytically for lower degrees n and numerically for higher degrees. We can notice that: those equilibrium probabilities can be pre-computed as a function of the relevant parameters (number of neighbors and cost-to-benefit ratio) and efficiently utilized by every node for further use. Thus, given the parameters, the node knows what probabilities to adapt to keep the overall system on a statistically stable state. Then, a simulation has been conducted to study the dependence of the solution $x_C^{(*)}$ from the perspective of w and M .

The curves in Figure 5.1 show $x_C^{(*)}$ vs. w for different values of M ($M = 2, 4, 8, 10$). We note that the equilibrium probability of candidate CH decreases as w increases. It will be more rapidly drops for larger values of M . This indicates that the benefit for being a candidate CH drops as w and the number of nodes increase, and each node tends to wait for some other nodes to perform the task of sending data on its behalf. On the other hand, when w gets smaller, ($w \rightarrow 0$) the nodes' probability of announcing as candidate CHs is high ($x_C^{(*)} \rightarrow 1$).

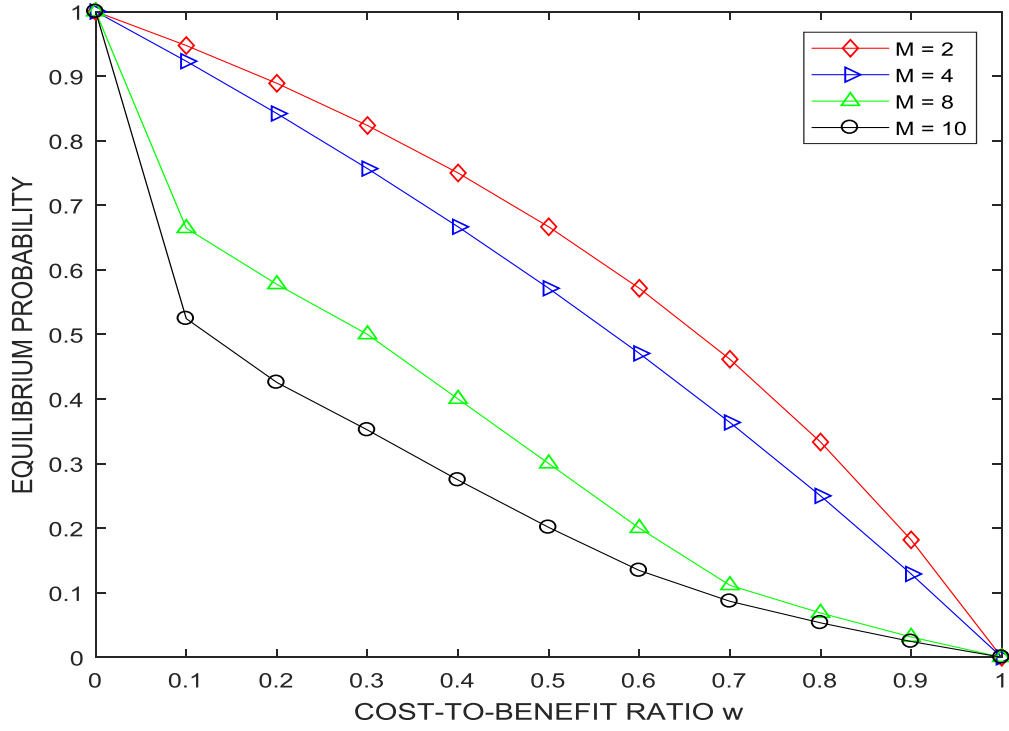


Figure 5.1: Equilibrium Probability (Probability of Volunteering as Candidate CH) as a Function of the Cost-to-benefit ratio w

The curves in Figure 5.2 show $x_C^{(*)}$ vs. M with respect to the different values of w ($w = 0.1, 0.3, 0.5, 0.9$). The results show that the equilibrium probability of candidate CH decreases with increasing number of nodes. The decrement is more as w gets increases. That is, the higher the number of nodes, the less the probability that a node is willing to announce itself as CH.

Thus, we believed that the designed evolutionary cluster-game is an appropriate model because it brings the population of nodes into a stable equilibrium. In such scenarios, over round, nodes learn how to perform well in practicing with a set of strategies and reacting to their observations. Considering the stable analysis (i.e., equilibrium probability), then, we have proposed a localized cluster-based algorithm. In the next section, the detailed description of GREET algorithm will be presented.

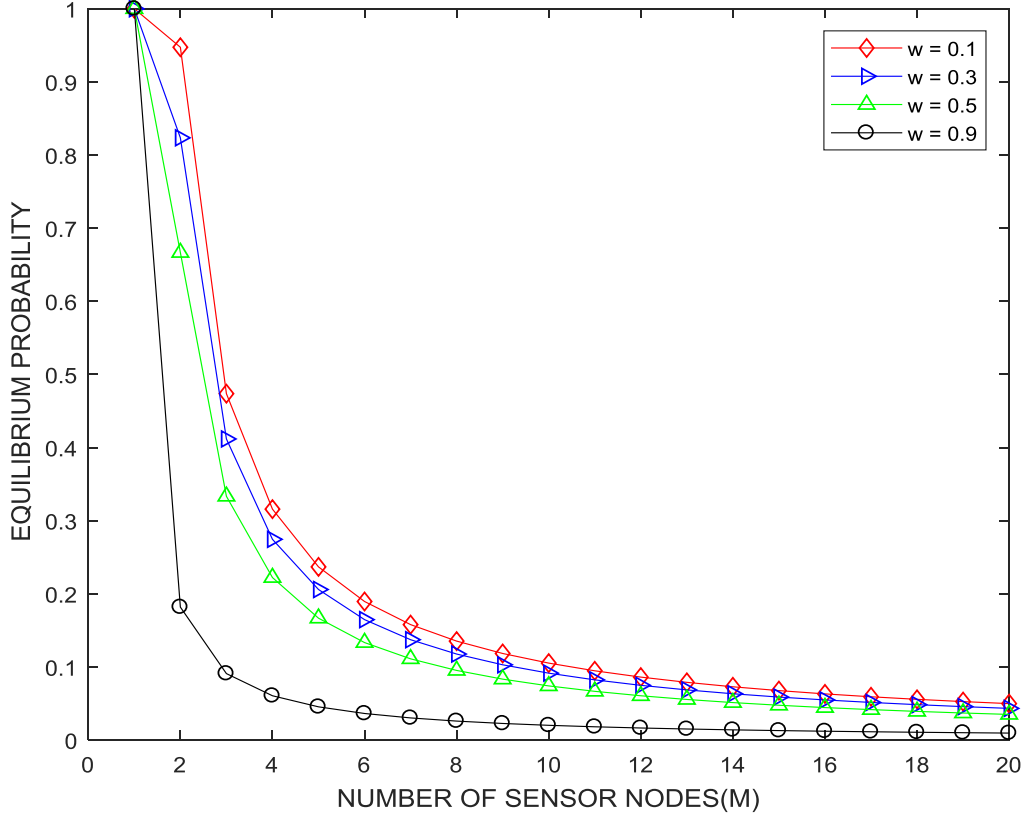


Figure 5.2: Equilibrium Probability (Probability of Volunteering as Candidate Cluster Head) as a Function of the Number of Nodes M

5.3 The Detailed Description of GREET Algorithm

Here, we present our Cluster Head determination algorithm, the GREET algorithm, inspired by the evolutionary cluster-game studied above in Section 5.2. Such an evolutionary game runs in each of the cluster autonomously and in parallel with the others when the equilibrium locally reached between nodes. The algorithm is part of a specific operational phase of sensor nodes life cycle. Such a life cycle – starting after node placement over the field – is typically structured into a self-organized initiation phase followed by a number of cyclic operational phases. The next phases, in the cluster-based algorithm, are the cluster set-up phase and the data communication phase, as shown in Figure 5.3. The set-up phase is subdivided into candidate CHs bidding, CH determination, and cluster formation. The data-transmission phase consists of data aggregation and transmission activities.

GREET operates within the candidate CH bidding sub-phase and the CH-determination sub-phase, in which it has been extended from CPF algorithm. In the current algorithm, we focus on the development of these two sub-phases in order to improve the limitation we previously encountered. Thus, evolutionary based GREET algorithm will be executed locally to mitigate selfishness. For the remaining phases of life-cycle, the earlier assumptions will be held.

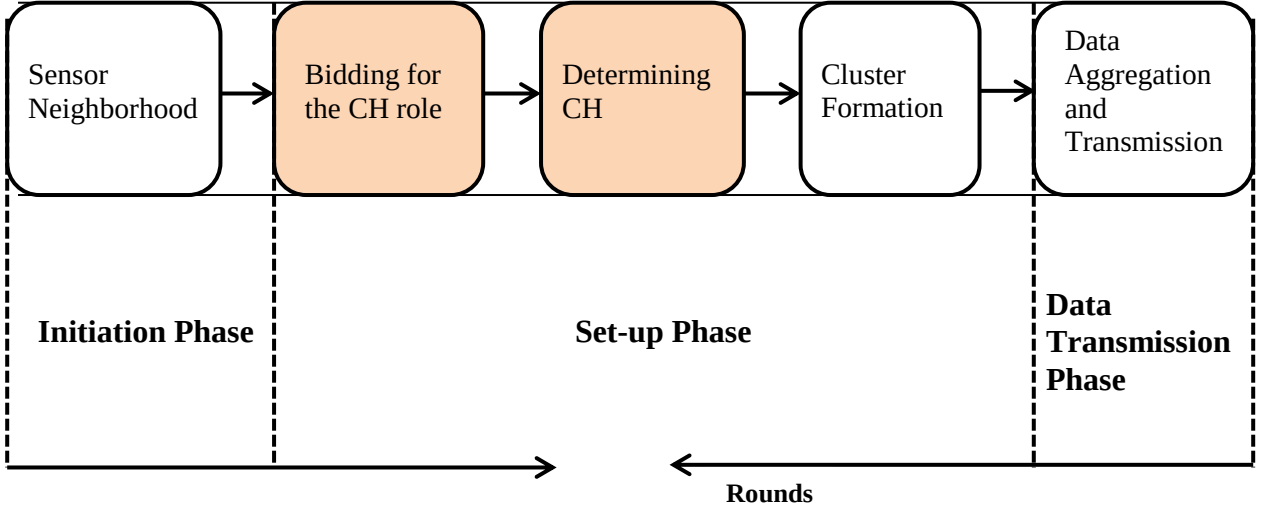


Figure 5.3: Phases of GREET Cluster Routing Algorithm

5.3.1 Initiation Phase

After the deployment of the sensor nodes, which we assume a uniform random, a set of nodes has to undergo a self-organization phase [164]. Nodes start the initiation phase by collecting statistical information about its neighboring nodes, in addition to broadcasting its own within radio coverage range also called communication range. We assume that each node can broadcast its data in low-power consumption short-range mode or in high-power consumption long-range mode. The latter is used when a node is CH to send its data to the BS. For the sake of simplicity, we assume all the nodes have the same power for the short-range mode and the same high power value for the long-range mode. In ideal conditions, this translates into all nodes the same short-range distance (R_{contest}) and the same long-range distance (L_{contest}).

The R_{contest} represents the largest transmission distance that a node can reach when it is a non-CH in order to gather the information about its neighbors. Thus, the participants are the node itself and its neighboring nodes lying within this radius.

During its initial deployment, any node will announce its existence known to its neighbors since it wants to use the other nodes' resources to send its data to the BS. By so doing, it aims to save its own energy. Otherwise, if it does not announce its existence to its neighbors, it will be unable to pass its data through the regional CH.

A node is expected to broadcast a simple GREETING_MSG message to make its availability known to its neighbors. The message also helps this node to learn the information about its neighbors. GREETING_MSG contains SENSOR_ID and node's ENERGY_LEVEL, its format is shown in Figure 5.4. In this phase, each node also counts the SENSOR_IDs that it receives from its neighbors and records as N_h .



Figure 5.4: A Simple GREETING_MSG Message Format

We denote $N_h(N_i)$ the number of neighboring nodes N_i , namely the number of nodes that one can sense at certain round. The topological arrangement of nodes is illustrated in Figure 5.5. The circles respectively represent the different competition ranges R_{contest} of nodes N_1 , N_2 , and N_3 . For instance, $N_h(N_1) = 6$ for node N_1 , $N_h(N_2) = 4$ for node N_2 and $N_h(N_3) = 6$ for node N_3 . As such, when M is the total number of nodes in the cluster game, $M = N_h + 1$.

At the end of this self-organizing phase, all nodes can be fully aware of the information about their neighbors within R_{contest} transmission radius.

5.3.1 Set-up Phase

A node can be in one of the following states, with respect to the CH-determination goal: CH-enabled, CH-disallowed, candidate CH, non-candidate-CH, appointed-CH, normal state, and loner state. At the beginning of every set-up phase, all sensor nodes are in the CH-enabled state, except for the ones that served as CH in the previous rounds, which are CH-disallowed.

A) Bidding for the CH Role

As the set-up phase starts, each CH-enabled node can explicitly announce the C-strategy (and become candidate CH) or tacitly adopt the Nc-strategy (and become non-candidate CH).

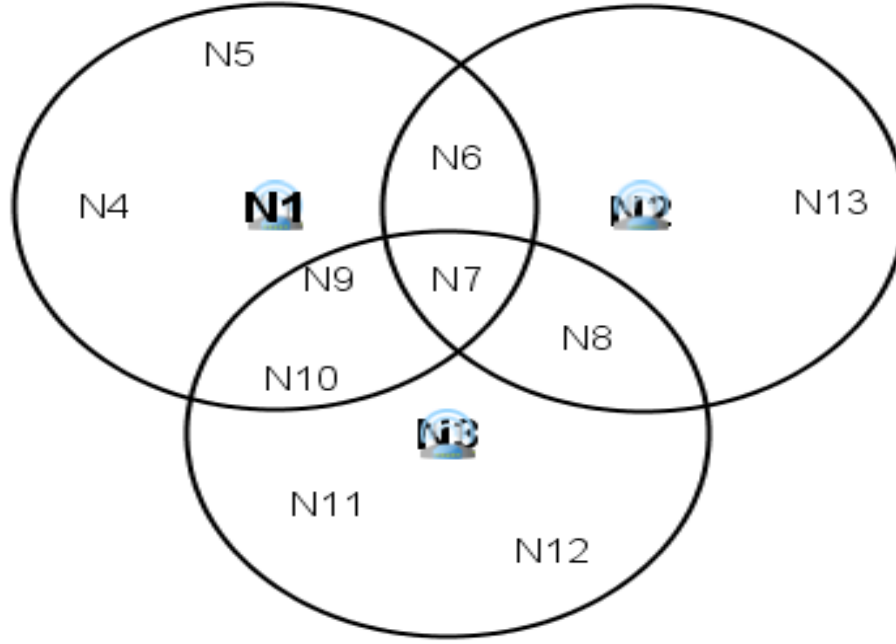


Figure 5.5: Representation of Radio Transmission Range ($R_{contest}$) for Nodes N1, N2 and N3

These nodes are in the $M = Nh + 1$ node game, as the one described in the previous section, which admits an ESS. In the well-mixed population hypothesis, we have seen that whatever the proportion x_C adopted at the starting would lead to the stable ESS equilibrium. Here we consider that, since the beginning, the nodes adopt the collaborative strategy with probability $x_C^{(*, M)}$. However, even if this is not the case, the mechanism of adaptive learning from interaction with the neighbors drives the system towards equilibrium. This finding has been confirmed by simulation.

Accordingly, although the nodes act non-cooperatively toward the other during their initial deployments; they adjust their strategies later as they reach a state of dynamic equilibrium. Thus, the nodes prefer to collaborate at $x_C^{(*, M)}$ probability in order to receive a better payoff. In these ways, specific nodes announce themselves as candidate CHs in their respective region while the others do not. This should occur for the purpose of keeping the proportional nature of stable equilibrium that the C-strategy and the Nc-strategy nodes have in the population.

As it was already stated, this implies that the proportion of these nodes will vary over the time of evolutionary changes. In this regard, the subpopulation of C-nodes increases if their payoff is bigger than the average payoff of the nodes' population; otherwise, their proportion decreases.

In other words, the proportion of candidate CHs announcement will grow up in the next round if the announcement in the current round results in a better payoff and vice versa.

Considering the behavior of nodes toward maximizing their own payoff, sometimes there is a possibility of getting more than two candidate CHs in the nearby region. This happens when more than two nodes won the contest game without recognizing each other. It is assumed that the announcements of nodes might be done almost at the same time interval. In anyways, this brings too many candidates in the same region. In this context, there might be a chance of getting more than two appointed-CHs. This means that in the same competition region, several nodes might be found as a CH redundantly.

Obviously, the presence of several CH nodes in the same region affects network performance. These CHs are unnecessarily exhausting their critical resources that will be on the way to diminishing their lifespan. In fact, the GREET algorithm shall reach an optimal nodes resource utilization, however, only where one node represents its member nodes as a CH in the nearby region. In light to the current appointment, all the remaining nodes that must share the same transmission region must be expected to join as a member node rather than staying as CHs. Considering these consequences, all of the present candidates must contest further for determining an actual CH. This latest competition, therefore, tackles the problem of getting more than two CH appointments. The solution will be discussed in the next section.

B) Determining the Actual CH

This sub-phase is important in order to ensure the optimal nodes resource performance that the GREET algorithm needs to achieve. Only one CH node is permitted to be present in the same communication region at a time. Hence, the candidate CH nodes have to further compete to set a chance to become the actual CH if they are more than two. In due course, an appointed-CH is the one with the highest residual power. In the hypothetical case of a tie, the contention can be resolved by randomization.

If only one sensor node plays C, that node becomes CH (and passes to the state of appointed-CH). Notice that, since appointed-CHs are at least at a distance R_{contest} meters away from each other, GREET can reasonably and uniformly distribute CHs over the field (i.e., provided that nodes are scattered approximately uniformly over the field).

The average energy of the network is just considered as a reference model for node to contemplate its interactive strategy at each round. As a result of such analysis and then, the strategy adopted, the nodes receive a certain payoff. To keep the network alive to the greatest extent as possible, it is truly an energy that these nodes need to own during communication. In such situation, at every round of transmission, the energy of the network is almost uniformly consumed. As a result, ideally, in this routing algorithm, the communication energy of individual nodes is drained near to the same round. It is also the target of the algorithm to balance energy utilization among the nodes collocated. Hence, our algorithm has to retain into this achievement in order to be considered as an energy-efficient routing algorithm: all nodes die almost in the same round that extends the individual's lifetime.

The corresponding state transition diagram that is determining an appointed-CH is shown in Figure 5.6. In this manner, the role of CH could be fairly distributed and shared across sensor networks. The algorithm could simply achieve this performance by localizing the competition of CH-determination. The nodes with minimum energy will be exempted from the competition (such nodes will stay in CH-disallowed state). In the next round, the node that served as an actual CH in the current round would not be allowed to return into CH-enabled state until its residual energy is no more a minimum.

Then, once the CH candidate confirmed itself for an actual CH, it has to broadcast its announcement to its neighboring nodes. After receiving an actual CH announcement, the other candidates in the same region will stop to compete for the same. Rather, they all return to the normal state and update their respective payoff function. As such, non-candidate CH is requesting to join the currently determined actual CH. It broadcasts JOIN_ACTUAL_CH message. Then, the nearest actual CH accepts the request by assigning a time to communicate packets.

Therefore, even though there might be several candidate CHs that have been announced close to each other, there will be only one actual CH that has to be appointed in the end. This indicates that the determined CHs are at least R_{contest} meters away from each other. As a result, the distribution of CH appointment is uniform while its role is fairly alternated between nodes since it considers nodes' residual energy.

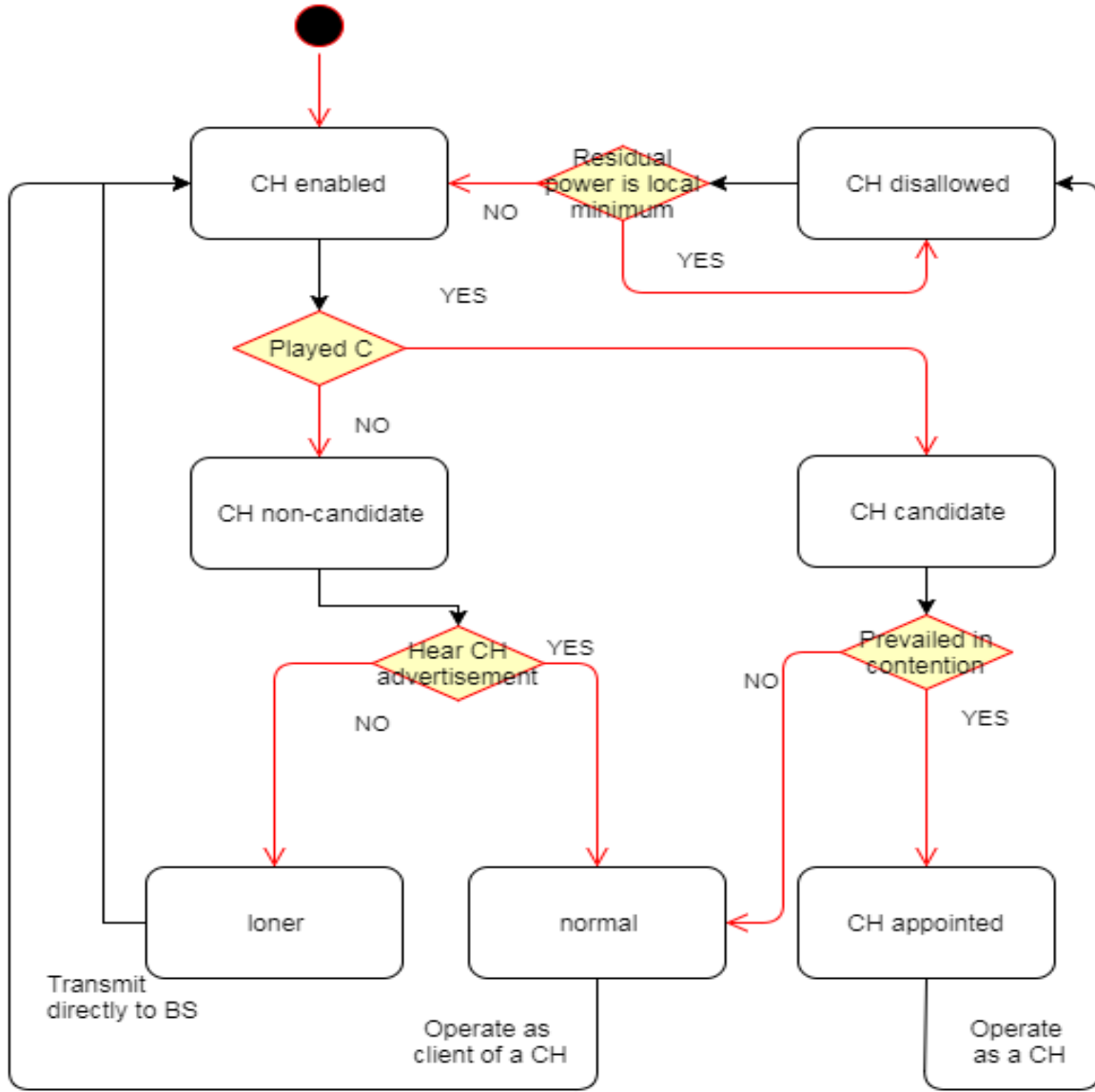


Figure 5.6: State Diagram for the Sensor Node

We assumed that GREET algorithm achieved an optimal resource utilization when there is only one actual CH representation in R_{contest} range of nodes. Therefore, let us evaluate such achievement for CH determination. Consider that S contains the set of all nodes in the region, $\forall s_1 \in \text{actual-CH}, \forall s_1 \in S$, also assume that C_{s_1} contains s_1 and s_2 candidate CH nodes that are in the same R_{contest} coverage range (i.e., every candidate can hear the simple GREETING_MSG from one another). As such, $s_2 \in S$.

In contrast, we assume that there is a candidate CH $s_2 \in C_{s_1}$ that is also contesting in the same range to become an actual CH, in which it also got granted. In due process, actual CH is

determined from the candidates, as the one having maximum remaining energy (e), if there are more than two candidates, thus, for $\forall s_3 \in C_{s1}$, $e_{s1} > e_{s3}$. In the same manner, if $s_2 \in C_{s1}$, then $e_{s1} > e_{s2}$ in accordance with actual CH determination.

As both nodes s_2 and s_1 are within the same range of R_{contest} , if s_2 is an actual CH then $e_{s2} > e_{s1}$; however, it is not since it is contradicting the previous assumption. As such, the correctness of determining only one actual CH in the same sensing region is validated. Therefore, considering, $\forall s_1 \in \text{Actual-CH}$ in which $s_2 \in C_{s1}$, there must be $s_2 \notin \text{actual-CH}$. Thus, it is provided that there is only one actual CH node in the R_{contest} range of GREET algorithm.

In this regard, there is no chance for two candidate CHs winning an actual CH competition if one is in the other's range. This means two nodes that were hearing the competition information from each other cannot be an actual CH at the same time interval. Thus, the availability of actual CHs in the network should be located at least R_{contest} distance from each other. It is the node that is having relatively an outstanding capacity to serve its neighborhood. Once it is served as a CH, such node returned back into CH-disallowed state where it can conserve its battery lifetime. In due process, sensor node will take the role turn-by-turn.

C) Cluster Formation

Once a node announces itself as appointed-CH, then the next step is a cluster formation. At this point, the appointed-CH advertises itself. The nodes receiving the advertisement go back to normal state and prepare to subscribe to that CH. In case of reception of more than one CH advertisement a node will prepare to subscribe to the one with the higher residual power. Now, CH-disallowed and normal state nodes send a message to their CH to subscribe as members.

The appointed-CH creates a time slot schedule and broadcasts it to all of its candidates, which – from this point on – become its cluster members. There can be also sensor nodes that did not bid for CH and that did not receive any CH advertisement: such nodes will not be able, during the current round, to route their messages through a CH: we call them loner nodes. They will remember this info and use it to play C in the following round. As to the current information to be sent by the loner nodes, any implementation of the algorithm should specify whether they should wait until the next round for trying to route the information or they should send the information to the BS directly. In the simulation below, we adopted the latter option.

At the beginning of the next round, all of the nodes in the normal state will become CH-enabled, while those that served as CH will become CH-disallowed. A node that served as CH in a round will return CH-enabled only when its residual power is not the minimum of its neighborhood; in the meanwhile, it will stay in the CH-disallowed state.

5.3.2 Data Transmission Phase

After cluster formation, the data transmission phase starts. The non-CH nodes initiate to send the packet to their nearest CH in relation to the assigned time slot (allocated TDMA schedule).

In fact, one of the main objectives of designing this algorithm is to improve the performance of MWSNs in the data transmission stage. Since nodes might generate significant redundant data packets, the CH; therefore, aggregates the similar data packets it received from multiple member nodes. Then, it sends the aggregated data packet to the BS for further decision making. Hence, the number of transmitted packets to the BS would greatly be reduced. As such, GREET algorithm utilized the communication bandwidth more efficiently.

5.3.3 Synchronization and Scheduling

GREET is an algorithm that can work under different settings and can be supported in different ways by infrastructural services: it is organized in phases and communication rounds, thus it assumes that a synchronization mechanism and a scheduling schema are provided. The choice of those depends on how constraining is the requirements of the application setting. A synthesis of the tradeoffs among the main synchronization schemas is provided in [165]. For the sake of simplicity, in the simulation, we assumed that synchronization is provided by broadcast signals from the BS. The results of the power consumption comparisons in the next section are expected to hold even under different synchronization schemas, provided that the involved cluster-based algorithms use the same schema.

As to scheduling, it depends on the varying degrees of structural organization available in the network during the different sub-phases. In the simulation, we assumed that, after the cluster has been formed, the scheduling can be coordinated by the CH, within a TDMA schema (as in LEACH): this avoids collisions and saves power. In the other less structured sub-phases, nodes should resort to contention-based schemas. As to the CH-to-BS communication, we assumed that scheduling is the responsibility of the BS.

5.4 GREET: Performance Assessment

In this section, the performance achievement of our algorithm is assessed based on equilibrium ability and energy utilization. The lifetime of an individual node that can form the networks, in an optimistic scenario, coincides with the lifetime of its battery. Toward that end, the nodes' energy utilization at stable equilibrium is examined. Lastly, the theoretical studies will be investigated for the number of players grouping in agencies interaction.

Sensor nodes consume their critical resource when gathering and transmitting the data packets. By its nature, transmitting the packets to an appropriate destination is a complex task for widely scattered devices. Several intermediate nodes are expected to transfer the packets until they reach the destination. Thus, our proposed algorithm provides an exciting solution to mediate the behaviors of such nodes.

The algorithm brings collocated nodes toward forming a common collaboration by adopting an equilibrium dynamics. The problem of nodes' behaviors would be tackled with an objective of preserving the energy of individual nodes during packet routing. As such, this algorithm groups the nodes into multiple clusters, when only one representative node is allowed at a time to transmit the summary of the packets that sensed in the same cluster. This process helps to minimize the energy consumption in a certain region. Hence, the cost of energy resources would be divided into intra- and inter-cluster communication in this algorithm.

The energy cost for the purpose of intra-cluster communication is an energy spent in the algorithm. It is the energy consumed by member nodes to transmit the gathered data to a nearby CH. After the nearby CH node is identified and the cluster is also formed, each non-CH node needs to consume a certain amount of energy to transmit a k bit of data packet. We assume a free space for propagation when the communication signal is in the line of sight with the receiver side and the multi-path fading propagation when the communication signal needs to pass for a longer distance.

In such consideration, we assume that during cluster formation the distance between the CH and the non-CH node is relatively short, i.e., d_{toCH}^2 (the non-CH uses E_{fs} to transmit the packet). Let E_{elec} is the energy dissipated by transmitter or receiver in order to process a k bit. Therefore,

in our algorithm, the energy spent by each of the non-CH nodes ($E_{\text{non-CH}}$) to transmit a k bit to its nearest CH is estimated as:

$$E_{\text{non-CH}} = kE_{\text{elec}} + kE_{\text{fs}}d_{\text{toCH}}^2 \quad (5.9)$$

On the other hand, energy is also consumed during inter-cluster communication. It is the energy spent by each CH node for the purpose of communicating the packets between its member nodes and the BS. Generally, this energy should be spent when the CH receives the packets from its member nodes, and aggregates those packets, and transmits to the BS.

In every round of our algorithm, the energy consumed by each CH node (E_{CH}) should be computed. In order to analyze this E_{CH} , we followed according to the works in [5], [6], [8], [91], [107]. Hence, one categorizes this energy into the dissipated energy by a CH to receive the packets of its member nodes (E_{Rx}), the energy expenditure to aggregate k bits packets (E_{Ax}), and the energy expenditure to transmit the aggregated packet to the BS (E_{Tx}).

The E_{CH} becomes:

$$E_{\text{CH}} = E_{\text{Rx}} + E_{\text{Ax}} + E_{\text{Tx}} \quad (5.10)$$

Let us consider that M is the average number of nodes inside a given evolutionary clustering game. We assume that the distribution of nodes is a uniform random. If we consider n clusters in the whole network, then there are $\frac{N}{n}$ nodes on average per cluster (one CH and $(\frac{N}{n} - 1)$ non-CH nodes). Thus, we assume that $M = \frac{N}{n}$ nodes.

Hence, E_{Rx} is calculated as:

$$E_{\text{Rx}} = kE_{\text{elec}}(M - 1)$$

Inside every cluster, there is an averaged number of nodes (one CH and $M - 1$ members). The energy spent by the CH to aggregate the packets of its members would be computed as follows.

$$E_{\text{Ax}} = kE_{\text{DA}}(M)$$

where E_{DA} is the data aggregation cost expended by the CH.

The distance between the CHs and the BS is also considered to be longer as the location of the BS is assumed to be far from the average location of nodes. Hence, the multi-path energy modeling (d_{toBS}^4 power loss) of the CHs must be used to transmit the packets.

So, E_{Tx} will be:

$$E_{Tx} = kE_{elec} + kE_{mp}d_{toBS}^4$$

In a nutshell, the total energy dissipated by the CH node for receiving, aggregating and transmitting a single frame to the BS will be:

$$\begin{aligned} E_{CH} &= kE_{elec}(M - 1) + kE_{DA}(M) + kE_{elec} + kE_{mp}d_{toBS}^4 \\ &= kE_{elec}(M) + kE_{DA}(M) + kE_{mp}d_{toBS}^4 \end{aligned}$$

The total dissipated energy in a single cluster in order to transmitting a frame to the BS will be:

$$E_{cluster} = E_{CH} + E_{non_CH}(M - 1) \approx E_{CH} + E_{non_CH}(M) \quad (5.11)$$

The total energy consumed in the network during a single round, E_{round} , will be expressed as:

$$\begin{aligned} E_{round} &= nE_{cluster} \\ &= nE_{CH} + NE_{non_CH} \\ &= k[2NE_{elec} + NE_{DA} + nE_{mp}d_{toBS}^4 + NE_{fs}d_{toCH}^2] \quad (5.12) \end{aligned}$$

where n is the number of clusters, N is the total number of nodes, d_{toCH} is the distance between CH and its member nodes, and d_{toBS} is the distance between CH and the BS.

The optimal number of cluster k_{opt} in given networks has been studied in LEACH_C [6], which has been extended from LEACH algorithm. This to say that at every round, the expected optimal number of actual CH that has been distributed by GREET can be analyzed.

Thus, one can compute by considering the derivation of E_{round} with respect to k to zero.

$$k_{opt} = \frac{x_m}{d_{toBS}^2} d_0 \sqrt{\frac{N}{2\Pi}} \quad (5.13)$$

However, the achievement of k_{opt} performance has directly been determined by the radio coverage range. We assumed in the simulation that nodes have the same $R_{contest}$. Thus, the optimized radio coverage that is represented as R_{opt} has to be addressed.

CH-enabled nodes should interact in their $R_{contest}$ short range to bid for candidate CH. Let us consider the equilibrium probability that a single collaborative node to announce itself as a

candidate CH is $P(\text{candidateCH})$. If n is the sum of such candidate CHs in the MWSNs, then, $n = P(\text{candidateCH}) * N$, where N is the total number of nodes.

If we assume m as the number of candidate CHs that have been represented inside R_{contest} then, m can be given as $m = n * \frac{\Pi R_{\text{contest}}^2}{x_m}$, where x_m is the x-coordinate.

In the network initial configuration, all nodes under consideration have been assumed to be homogeneous in their energy capacity and competition capability. Therefore, these m candidate CHs have an equal chance to contest and win an actual CH game. So, the probability that one candidate node wins an actual CH game in the R_{contest} , $P(\text{actualCH})$ should be computed as:

$$P(\text{actualCH}) = P(\text{actualCH}|\text{candidateCH}) = \frac{1}{m} = \frac{1}{n * \frac{\Pi R_{\text{contest}}^2}{x_m}} = \frac{x_m}{N \Pi R_{\text{contest}}^2}$$

Therefore, if $EX(|\text{actualCH}|)$ is the expected number of actual CHs, it will be calculated as:

$$EX(|\text{actualCH}|) = N * P(\text{actualCH}) = \frac{x_m}{\Pi R_{\text{contest}}^2}$$

The GREET cluster-based algorithm is expected to optimize the energy consumption of individual nodes. Its expectation would be realized by optimizing the number of actual CHs distribution. So, one considers that the expected number of actual CHs is equal to k_{opt} in the network, i.e., by assuming that $EX(|\text{actualCH}|)$ is equal to k_{opt} .

Then, by merging the k_{opt} into the above formula of $EX(|\text{actualCH}|)$, the optimal radius, R_{opt} is computed as follows:

$$R_{\text{opt}} = \sqrt{\frac{x_m}{\Pi k_{\text{opt}}}} \quad (5.14)$$

In the contrast of GREET algorithm, our previous work of cluster-based routing algorithm (i.e., CPF) assumed the interaction of whole nodes' population. The latter assumption is also taken by the earlier research works of these areas, CROSS [14] and CORE [16]. They assumed non-collaborative nodes behaving rationally to make an independent decision in the network. In these schemes, it was also assumed that the whole nodes of MWSNs interact with each other in the game by maximizing their own radio coverage. As a result, in such schemes, the distribution of CHs may be non-uniform. In addition, CH node was selected randomly for

which fairness could not be ensured between nodes. In such cases, the member nodes have to spend much more energy to communicate with their corresponding CHs that may be located at a far distance or the determined CH is an energy critical node. This concept is also true for LEACH algorithm, which assumes that nodes are always collaborating.

5.4.1 Energy Cost at Equilibrium Evolution

Sensor node plays either C or Nc strategy at the stable equilibrium stage. As such, C-nodes would be extended further into the competition of actual CH determination.

In the meantime, the nodes also need to estimate and execute certain cost that is shared in their respective R_{contest} coverage. The cost c of being a CH due to aggregating collected packets and transmitting to the BS is one of such cost that needs to be analyzed. In the context of this algorithm, the packets sent out by the nodes reach the BS either directly or through some intermediate nodes. As a result, sometimes the cost of packet transmitting might vary for some nodes. Whatsoever the methods applied, the factors such as packet size, the number of packets received by the CH (the number of its member nodes), and the distance between the CH and the node that will receive the packets are generally determining the values of c .

Thus, let us represent approximately, the value of parameter c according to such factors. The value of parameter c is estimated according to the competition range. Meanwhile, it is already considered that the packet has always the same size in our algorithm, i.e., k bit large, regardless of the nodes under consideration. In addition, for our work, the average distance parameters and the average number of member nodes in each cluster are estimated according to the works of [97], [166]. The Poisson distribution of random variables was studied in [166], in which case, it was assumed that for homogeneous Poisson process, the distribution of each independent particle is uniform in the plane. Accordingly, the average distance d_{toCH} (the average distance between CH and its member nodes), and the average distance d_{toBS} (the average distance between CH and BS) can be estimated as.

$$d_{\text{toCH}} = \frac{x_m}{\sqrt{2\pi n}} \text{ and } d_{\text{toBS}} = 0.765 \frac{x_m}{2} \quad (15)$$

Hence, an average distance would be computed for each d_{toCH} and d_{toBS} separately, when N nodes are uniformly distributed in $(x_m \text{ by } y_m)$ sensing field and the BS is located at the center of the field. It is also assumed that in Poisson distribution the nodes form a cluster with an equal

average number of nodes inside the nodes' R_{contest} . Thus, in every range, we assume that the determined CH should receive the same number of data packets from its member nodes, probably in which case it consumes nearly the same amount of communication energy.

In addition, a node with a better utility value or residual energy should be always in the competition of CH-enabled state. Every appointed-CH is located in the distance of R_{contest} range. The role of CH is also cordially rotated in the network. So, as it is already assumed the average distance for each CH in the region from the BS is $d_{\text{toBS}} = 0.765 \frac{x_m}{2}$. This is providing us to set out what would be happening in the process of an actual CH determination. After certain communication rounds, sensor nodes that are found in the given region are expected to balance their energy level. In the same context, the energy cost of being a CH for the nodes in the same range R_{contest} should be expected to be similar. Hence, the cost c will be locally almost the same for nodes that are found in the same competition range, i.e., $E_{\text{CH}} \approx c$.

The other parameter that needs to be determined is the energy cost of communication (μ) by each non-CH node (i.e., member node) in transmitting its sensed raw data to its nearest CH. Usually, the value of μ depends on the distance each node has from its respective CH as well as the size of the data packets (assumed to be the same: k bits) this node needs to transmit.

Let us represent the distance node j has from its CH as $d_{j\text{CH}}$ and the energy cost of this node as μ_j . As the CH node is determined, the distance $d_{j\text{CH}}$ might be a bit different in each round of communication. Thus, μ_j may be different that needs to be estimated. However, since the nodes join a CH node in their respective R_{contest} as well as the role of CH appointment is also rotated among those nodes inside this range. Thus, it is possible to assume that a non-CH node has the same average distance from its CH. The CH workload alternates between these nodes. In such condition, the individual distance parameters are also assumed to be almost the same for every node after some rounds. As a result, there is no reason to assume the energy cost of an individual node to transmit its packets to the nearby CH to be the same after some rounds, thus, $E_{\text{non-CH}} \approx \mu$.

Therefore, at an equilibrium state if we consider the energy consumption of an individual node as $E_{\text{non-CH}} \approx \mu$, and the energy dissipated by a CH as $E_{\text{CH}} \approx c$.

$$c = E_{\text{CH}} > E_{\text{non-CH}} = \mu \quad (5.16)$$

Then, we may reevaluate the probability of a node volunteering itself as a candidate CH in the M-node evolutionary game. So, when nodes reach an optimal stable equilibrium, the cost-to-benefit ratio of GREET cluster-based algorithm which was previously analyzed $\frac{c}{b} = w$ will be amended as, $\frac{(c - \mu)}{(b - \mu)} = \delta$, where $(0 < \delta < 1)$. Accordingly, the previous assumptions of nodes existence at an equilibrium dynamics will be reclaimed. Here, the actual cost and benefit obtained by the nodes will be analyzed. The actual benefit of Nc-node is $b - \mu$ instead of b while at least in its neighbor there is a C-node, since in the actual case: this node has to consume its energy to transmit its sensed data to the neighboring CH. In the same manner, for a node that is playing C-strategy (i.e., C-node) the cost of performing CH task will be $c - \mu$, instead of c . Consequently, at a local equilibrium, nodes evolution (as of Equation 5.8), the nodes bidding or no bidding for CH role becomes:

$$x_C - 1 + \frac{(c - \mu)}{(b - \mu)} \sum_{k=0}^n \binom{n}{k} x_C^k (1 - x_C)^{n-k} \frac{1}{k+1} = 0$$

Thus, by substituting, $\frac{(c - \mu)}{(b - \mu)} = \delta$:

$$x_C - 1 + \delta \sum_{k=0}^n \binom{n}{k} x_C^k (1 - x_C)^{n-k} \frac{1}{k+1} = 0 \quad (5.17)$$

Hence, the equilibrium probability $x_C^{(*)}$ is derived for our evolutionary cluster-game. Deciding whether to volunteer as a candidate CH or not is a symmetrical mixed strategy for nodes in order to receive the same benefits. This means for a set of CH-enabled nodes that are located in the same R_{contest} , a cooperative operation is a natural phenomenon. Therefore, mutual network operation is naturally developed by this dynamic evolution. Any mechanism of cooperation enforcement (such as a reward) might not be required in this algorithm. The message overhead would have much more increased if such mechanism had introduced. That would have affected the network performances much.

N-nodes need to broadcast a simple GREETING_MSG to announce their existences in the course of initialization phase. After these announcements, every node learns the information about its neighboring nodes. Hence, CH-enabled nodes evolve and execute the equilibrium probability at a local level in order to announce themselves as a candidate CH. Suppose K

numbers of nodes decided to announce the message CANDIDATE_CH_ANM at the equilibrium probability $x_C^{(*)}$ that should be shared with other nodes in the same R_{contest} region. As such, determining actual CH in the given region will be the next phase.

Hence, from accessible CH candidates (if they are more) that interact inside the same R_{contest} , a single candidate should be allowed to win the actual CH competition. Assume the number of appointed-CHs is T_c . Such appointed-CHs are broadcasting an ACTUAL_CH_BRD message.

So, the non-candidate CH nodes that hear an ACTUAL_CH_BRD message shall request to join the nearby actual CH. In so doing, they broadcast a JOIN_ACTUAL_CH message. Thus, $N - T_c$ numbers of non-candidate CH nodes need to join their nearby actual CH during the current cluster formation. Lastly, the data transmission schedule is assigned to all non-candidate CHs nodes in the surrounding of each appointed-CH. Once again the number of actual CHs that wish to broadcast a TDMA_SCHEDULE will be T_c .

The total number of messages overhead becomes, $2N + K + T_c - T_c + T_c = 2N + K + T_c$. Thus, our GREET algorithm has $O(N)$ asymptotic order.

In general, the issues of message complexity for GREET routing algorithm is resolved by adjusting equilibrium probability $x_C^{(*)}$. If an ample number of candidate CHs enters into the competition, a good quality of actual CH distribution would be expected. Since it has already been noted in the above analytic evolutionary dynamics (Section 5.2.2) the number of candidates K were estimated in accordance with the $x_C^{(*)}$.

The maximum value of $x_C^{(*)}$ should produce too many numbers of K , and as a result, produced message overhead should be increased. Such issues are particularly observed when active nodes located in the certain region started to die. As the number of these nodes has reduced, their $x_C^{(*)}$ has increased and that affects the distribution of nodes with remaining energy, which has been observed in the simulation, i.e., rounds at which all node deaths have been reduced.

On the other hand, when nodes reach small values of $x^{(*)}$, from those available nodes in the neighbors, less number of candidates has to announce themselves. This increases the number of nodes that adopt direct communication in the current round. In the due course, such nodes consume much energy that limits their lifetime. So, the message overhead of this algorithm

should be adjusted by guaranteeing a good quality of candidate CH distribution. In this context, the equilibrium probability of volunteering as a candidate $x_C^{(*)}$ has to be adjusted.

5.4.2 Players Grouping in Agencies

In order to challenge the capabilities of our algorithms, so far we have analyzed the worst case scenario about nodes' representation. In such context, we assumed that each node represents an agency by itself in the evolutionary dynamic model. As a compliment, in this section, we model analytically the case where more nodes can belong to the same agency. In that case, the selfish player is the agency: nodes from the same agency behave collaboratively, forming a coalition whenever they happen to be in the same cluster.

Here we outline such a generalization in terms of the analytic model. The change with respect to the previous setting is that if two or more sensor nodes belonging to the same agency meet in a region, they must collaborate with one another, i.e. form a coalition, adopting a coordinated strategy behavior. We denote coordinated coalition strategies with a hat sign. A coalition can play $\hat{C}$ or $\hat{Nc}$. Playing $\hat{Nc}$ for the coalition means that all the members play Nc ; playing $\hat{C}$ at coalition level, means that only one chosen member plays C and the remainder play Nc .

Let us indicate by G the number of agencies – each agency being indexed by g , and let N_g the number of sensor nodes of agency g ; let the total number of sensor nodes be $N = \sum_g^G N_g$. So far, we had assumed $N_g = 1$, i.e. $G = N$. Now we allow $1 \leq N_g < N$. Hereafter, we compute the payoffs in those scenarios; furthermore, we discuss the impact of the payoff on the replicator equation and on the equilibriums. Notice that in the payoff computation we take the point of view of the agency (as, in fact, we already did in ECG model, where $N = G$).

An important point is that the dynamic system can depend on whether we are assuming that the players are aware of each other's affiliation before announcing their choice (informed choice) or not (uninformed choice). The former case corresponds to the setting where the information about the owning agency is broadcasted with the Hello GREETING_MSG, which precedes the announcement; the latter case corresponds to a setting where that information is broadcasted at the time of the announcement.

Hereafter, we assume that the nodes broadcast their agency affiliation with the Hello GREETING_MSG, i.e., in the informed choice setting. It follows that nodes can adopt some

form of inter-agency collaboration before making their choice. A simple collaborative model consists in assuming that nodes have some way of agreeing on a common strategy with the members of their agency (either by predetermined rules or with a round of further information exchange or negotiation). In this case, each coalition can behave as a single (“extended”) player.

What counts, thus, is how many times the extended players, i.e., distinct coalitions, meet in a round: we fall back to the case of many-player interactions, except for the fact that the number of players is equal to the number of non-empty coalitions involved in the interaction and that this number fluctuates from one round to the next, a formal statement of the solution strategies follows. Assume that, at each round, clusters are formed by drawing M -players at random from the population. The fact that they are owned by distinct agencies determines a partition of the M -player set: each partition block is a coalition with k_g elements belonging to the same agency g . Let $K = \text{card}(\{g \in \{1, 2, \dots, G\} \mid k_g > 0\})$ the number of the agencies actually represented in the M interacting player set of a round.

Let us consider the point of view of a coalition g' , represented by, at least a player. The nontrivial equilibrium strategy, for a player belonging to agency g' , depends on the following conditional strategies. At the beginning of the round, we should find out $k_{g'}$ and k ; if $k_{g'} = 1$, i.e., there are no agency-fellows, play C with probability $x_C^{(*, K)}$, solution of Equation 5.8; if $k_{g'} > 1$, i.e. there are agency fellows, agree with them a common strategy, so that the coalition plays $\hat{C}$ with probability $x_C^{(*, K)}$, Equation 5.8.

5.5 Summary

In this chapter, GREET, an energy-efficient cluster-based routing algorithm is proposed to model the behavior of individual nodes that randomly engage in group-wise interactions. Such interactions have been done by individuals in their independently formed group. In this context, individuals change their strategies in accordance with the observations about their neighbors. The decision of individuals is in line with comparing their relative advantage provided by an average payoff. As such, they achieve a stable equilibrium to adopt the strategy that performs better in the aspect of replicator dynamics.

The proposed GREET algorithm executes in round. The studied analytical stability has been confirmed through accompanied by numerical simulation that both C-nodes and Nc-nodes could co-exist in the clustered population. The primal advantages that are achieved in GREET are, thus, summarized as follows:

- i. **GREET Algorithm is a Fully Distributed:** Individual nodes interact independently with each other through localized communication. In the course of this interaction, these nodes share their own information, and also learn the information about their neighbor. This is the initiation phase where nodes gather the overall information they need to analyze in order to participate. Then, the dynamic equilibrium strategy reached when everybody agrees to adopt it, in order to get better benefit in packet transmitting. As such, the stable equilibrium brings up some partial nodes for candidate CHs announcement. Hence, the algorithm procedure is a distributed where node autonomously chooses how to perform well.
- ii. **Low Control Overhead:** In the context of sensor networks, the broadcast nature of the medium must be taken into account. The battery-operated nodes consumed their important energy during this message overhead. Hence, it is desirable to reduce the control overhead of nodes to extend the time of data gathering. It has been shown that this algorithm has an asymptotic order of $O(N)$ control overhead. This makes GREET algorithm better in message overheads when compared it with others, namely CPF, CROSS, and CORE. In the former algorithm, the nodes consume less resource since their interaction should be limited to R_{contest} range. In the latter case, the computational, and the operational cost of CH-determination will be high since the whole nodes are interacting globally. Such a global interaction is obviously unrealistic, for a tiny node that has limited power coverage. In addition, such a larger transmission distance consumes much more energy on radio communication which also brings in more signal interference.
- iii. **Energy Balanced Clustering Mechanism:** The algorithm harmonizes the energy utilization since packet routing workload is equally distributed and shared among every node. This would be executed at the equilibrium dynamics of individual nodes in which they are expected to track their resources in relation to their neighboring nodes. At these equilibrium strategies, each individual adjusts its behavior of participating in the routing algorithm by considering the information of its neighbors in addition to evaluating its benefit and cost. In due course, this

individual sets whether to contribute to the algorithm or not at the local level. Such an equilibrium adjustment by itself is also balancing energy consumption.

GREET algorithm would balance the energy consumption of CH nodes in two techniques: a) Local CH distribution; b) Rotating the workload of CH

- a) **Local CH distribution:** The nodes which determined as an actual CH to represent its neighboring node is at least R_{contest} meters away from other CHs. It is expected as a node that has a better residual energy. The operated-CHs should uniformly be distributed relatively at an equal distance in the network. Thus, the distribution of nodes in the formed cluster is obviously harmonized so as to balance the workload among CHs.
- b) **Rotating the workload of CH:** The node that has served as a CH in the previous round would be exempted from the current competition. This node must stay in the state of CH-disallowed until its remaining energy is not the minimum in comparison to its neighboring nodes. It is an idle state when such node conserves its battery lifetime by sending its packets through others. In this manner, the role of actual CH is well rotated and adjusted among the neighbors in their R_{contest} .

CHAPTER SIX: PERFORMANCE EVALUATIONS

In this chapter, we demonstrate by simulation that, the proposed algorithm takes the dynamic system to equilibrium, in analogy to what happens with the analytic model. Accordingly, network performance evaluations have been subsumed for validating and assessing our analytic model in more a realistic aspect. The performances of our cluster-based routing algorithms have been evaluated by considering the residual energy, the network lifetime and the packet throughputs.

The chapter is organized as follows. The overview of simulation is discussed in Section 6.1. The basic simulation assumptions and parameters of network setup along with network evaluation metrics are provided in Section 6.1. The analyses of simulation results are discussed in Section 6.3, and finally, the summary of the chapter is presented in Section 6.4.

6.1 An Overview of Simulation Systems

Even for moderately-sized sensor networks with tens of nodes, it is impossible to judge the performance of the algorithm by studying it only theoretically. In this case, network simulation is considered in order to validate the algorithm implementation in practically. This is the common methodology used to evaluate different network algorithms and test the applicability of new theories and hypotheses. Therefore, for the purpose of determining the desired behaviors of a dynamic equilibrium in our algorithms, we have conducted a simulation that has been assessing network performances.

Modeling techniques will be used since the behavior of the nodes is faithfully imitating the response to the system. This has been considered according to equilibrium state data of our analytic model. So, the representative data model will be considered in the simulation due process. With this representative equilibrium, the experiments will be conducted with the aim of understanding and analyzing the behavior of the real scheme. In this respect, a model of nodes behaviors has to be adopted. The possible strategies of nodes for packet routing are also incorporated into our simulation. As such, the extent of each node's behavior has to be studied in the population of nodes' game. Then, the performance of the system will be evaluated at equilibrium dynamic with the purpose of controlling the behaviors of nodes.

6.2 Basic Scenario-Specific Assumptions and Estimations

a) System Network Setup

Our systematic simulation setup considers MWSNs which consist of $N = 100$ nodes. They are static after deployment. For the purpose of nodes' application domain, we have simplified our simulation system that these nodes have a common BS. This means, the BS having an infinite energy, is a common resource for all authorities. It is placed at the center of the field, and accessible by all nodes, in which they are in long-range transmission mode. Nodes that are located in the same communication range are able to communicate with each other, even though they belong to different owners. If we assume that the deployed nodes are using reliable and symmetric packets communication channel, a packet is lost only if the sensor is misbehaving.

In the course of nodes' deployment, each node randomly sets what behaviors to adopt from the provided possible strategies. Initially, a node considers its behaviors either as cooperative (normal) or as non-cooperative (selfish). Instead of statically fixing the number of non-cooperative nodes, a random mechanism has been employed in our simulation, in which, a node determines its behaviors of interactions by itself. These nodes also have the same capacity to process it.

The parameters of hardware designing such as energy consumption and transmission range are selected according to [5], [6]. In line with these algorithms, a clustering topology of the sensor network is also identified. Table 6.1 shows the summary of simulation parameters.

Node's Deployment: This can follow either structured or unstructured manner in a real scenario. When nodes are deployed in a pre-planned position they establish a structured arrangement; otherwise, their arrangement would be unstructured. The former way of nodes' deployment has a higher initial cost and it is also infeasible for certain hostile areas of applications. In such locations, nodes are deployed in an ad hoc manner (for instance randomly dropped from a plane) to perform the monitoring and reporting functions. In our case, such a real-time application scenario was considered to deploy nodes in the simulative environment. In the same context, we deployed the nodes in a two-dimensional unit square region (x_m by y_m) by assuming a uniform random mechanism [166]. In this mechanism, one assumes that there are several independent points where each of them will be uniformly distributed over a region.

Table 6.1: Network Simulating Setup Parameters

Size of the region ($x_m \times y_m$)	100x100
Placement of nodes	Random
Number of Nodes Deployed	$N = 100$
Number of iterations	$r_{\max} = 2500$
Packet Size	$k = 4000$ bits
Initial Energy of Sensor Nodes	$E_0 = 0.5$ J
Data Aggregation/Fusion Energy Consumption	$E_{DA} = 5$ nJ/bit/report
Amplification Energy (Free space power loss), $d > d_0$	$E_{fs} = 10$ pJ/bit/m ²
Amplification Energy (Multi path fading power loss), $d \leq d_0$	$E_{mp} = 0.0013$ pJ/bit/m ²
Average distance of nodes from BS	$d_{toBS} = 0.765 \frac{x_m}{2}$
Average distance of nodes close to CH	$d_{toCH} = \frac{x_m}{\sqrt{2\pi n}}$
Parameter w is defined as cost-to-benefit-ratio	$(0 \leq w \leq 1)$
Parameter d is defined as reward-to-benefit-ratio	$(0 \leq d \leq 1)$

Number of Nodes: The overall number of nodes needed in our simulation has been assumed in accordance with the area of nodes' deployment. Thus, there are 100 nodes ($N = 100$) that were considered in our virtual reality of 100m by 100m size of the sensing region. Each node has a unique identifier number called SENSOR_ID.

Homogeneous Nodes: In this dissertation, we assume that the initial energy is uniform, and the computing power is the same for all nodes. They have equal capabilities in the evolutionary game involvement. Thus, sensor nodes compete equally in their due processes. As such, there is no external factor that can discriminate their competition.

Transmission Power: The quality of communications will be enhanced by adopting an appropriate transmission power. The radio transceiver is the main source of energy consumption in WSNs. In this process, the transmission power should be adjusted according to the node's

current needs. Such design techniques will decrease the energy consumption and signal interferences effectively and result reduced packet collision and prolonged network lifetime.

Transceiver and antenna design are the parameters that must be considered in these designs. However, going into the physical details of wireless channels is beyond the scope of this study. Thus, we adopted along with the standards given in [5], [6], [97], [98].

Energy Dissipation Mode: Since the individual node is power-driven, there has to be a critical sensor network design to manage its energy. Concerning the issues of designing, in this case, the radio-energy model that was discussed in Section 2.2.2 has been considered. Thus, this model is widely used in evaluating the energy dissipation of nodes in the cluster-based algorithm for low-energy radio devices. This has also been assumed as a benchmark standard in the various currently ongoing researches of cluster routing designing.

Number of Neighbors: This is the number of sensor nodes that are located within other nodes' transmission range even though they belong to different owners. For instance, if one node broadcasts its information, individuals getting such announcement will be considered as its neighbors (this has been discussed in Section 5.3.1).

b) Simulation Environment

MATLAB software was developed by Math Works Inc., in which its name stands for matrix laboratory [167], [168], [169]. It is normally considered to be the best software package applied in order to study and analyze very large data. This can be attributed to its capabilities, flexibilities, and reliabilities combined with its powerful graphics. Moreover, it provides hundreds of reliable and accurate interactive functionalities that are built-in mathematically. Thus, these built-in functions are further used in the modeling of a broad range of our numerical equilibrium studies.

A previous study in [170] indicated that little differences in selecting a network simulator can actually bring about quite different results. Consequently, there is a possibility of reaching different conclusions. This is to emphasise the fact that extreme care has to be taken in selecting an appropriate network simulator in representing real scenarios. Conducting simulation is actually the most widely accepted mechanisms to investigate the practical aspect of networking communications. As such, the characteristics of the selected software in

capturing the performances of the model should be considered as such at the moment of deriving the model conclusions. Developing awareness about the selected software's potential performance and inconsistencies is also another issue to be considered.

In the current study, the aims of simulation were two-fold viz. analyzing the testability of the dynamic equilibrium system numerically, and assessing the validity of our proposed cluster-based routing algorithm in terms of network metrics. These should be done through analyzing the strategies of uncooperative nodes that will be followed by the development of cluster-based routing algorithm at the equilibrium dynamics of nodes. MATLAB is a more desirable network simulative tool as such to be considered for simulating and assessing our proposed scheme. In this case, the highest performance of MATLAB in numerical computation and data analysis will be utilized effectively. Accordingly, the complex and the largest numerical numbers of the dynamic evolution of our equations can be easily analyzed and interpreted. This is analyzed by visualizing the interpretation and association of the equilibrium stability state of the nodes.

Thus, these numerical results can be incorporated into the development of cluster-based routing algorithm that helps each node to adjust its strategies in packets communications. The behavior of a node in the algorithm should dynamically be captured and updated in the due process. In this regard, the strategy should be changed (between cooperative and non-cooperative) at every round of packet transmission. In these considerations, nodes in the modeling should straightforwardly interact with nodes in the population. In the same vein, their benefit and cost of strategic interaction for transmitting the packets should be analyzed. Furthermore, this software provides a fast and easy way of simulating the prototypes of the sensor network being its working interface is also user-friendly.

c) System Evaluation Metrics

This section discusses the set of network evaluation metrics that are used to evaluate the performance of our algorithms. In this regard, the objective of sensor networks deployment and their intended applications have been taken into account. Accordingly, the duration of nodes is an important issue that one needs to assume in sustaining the qualities of data sensing and transmission. It is the length of service time which the network is able to deliver effectively. This means the packets communication would be determined by whether nodes are available to deliver such services or not. This is an issue that is considered in the functionality of WSNs.

Thus, assessment of network lifetime is one of the most important and widely accepted metrics with respect to evaluating the performance of any proposed algorithm.

Several definitions of network lifetime have been provided in the literature. Some of them were considered as the time at which a certain amount of nodes die for the first time once a network started to function [14], [90], [171]. The time after which there is a region no longer covered by the network is also another definition that has been studied in [172], [173]. It is also defined as the time until exactly half of the nodes are alive in the network [16]. These definitions would be appropriated along with the various applications of sensor networks although the one that might fit into the latter two definitions are very limited.

The definition that makes more sense and which was applied in our study is the time when the first node dies in the network. Therefore, in our simulation analysis, network lifetime was measured in terms of the round when the first node dies as a result of depleting its energy. That is the numbers of rounds that the BS would continue to receive data packets from all sensor nodes. This is also considered as a time period in which the network is expected to provide a stable service.

If a node in the network dies, sometimes it would be unrealistic to assume that the remaining network will perform well. A likely reason could be that any data packets cannot reach the BS from that area where the responsible node is dead. Besides, this may lead to an early partitioning of network architectures into two or more where there are certain nodes' data packets that could not reach the intended destination. Obviously, this, in turn, reduces the packet throughputs. The time interval between the first and the last node dies is also assumed to be the network unstable period.

In this case, to assess the performance achievement of our algorithms, mainly, we are motivated by the network lifetime as the node that first runs out of power (First Node Dead time, or FND). This is directly related to the network's energy conservation plan. When a node runs out of power, the network cannot fully perform the tasks which are assigned to it. This may affect the overall service qualities. Additionally, in order to elaborate on the efficiency of our routing algorithms, we have considered Last Node Dead (LND) and residual energy of the network. Here, the former will be defined as the round at which all nodes drain their batteries

while the latter is the number of nodes with positive residual energy. The residual energy of network measures the total number of nodes' distributions that are still alive.

In the end, the performance of our algorithm is evaluated using packet throughput metric which is the total amount of data packets sent over network by sensor nodes [173]. It includes the packets that are sent from nodes to the BS, in addition to the packets sent from CHs.

6.3 Simulation Results and Discussions

In this section, the evaluation result of our analytic based algorithm will be presented along with the other standard cluster-based routing algorithms, viz. CROSS and LEACH. For such algorithms, their output data been reported along with the payoff parameters that have been taken randomly from the analytical model.

The evaluation performance has been measured according to LND, FND, networks' residual energy, and packets throughput. The discussion for such algorithmic comparisons is represented as follows.

a) Cluster-Based CPF Algorithm

This algorithm has been evaluated according to the main parameters w and d . As it has been stated in Section 4.5.1, the CH (also called Forwarder-head) is selected from C-nodes. Once it is announced the other nearest nodes will join it as members in their respective communication range. CH is also rotated among the potential nodes by computing their collaborative history. Energy consumption is fairly shared among all nodes to improve the network lifetime. This improvement should be maximum when the cost of cooperation is less, as well as the incorporated rewarding, is maximized. In this process, a node will be vastly interested to form collaboration in order to retrieve its own utility. This shows that cooperative packets communication among non-collaborative nodes could by far improve the network performance.

Considering the different values of w , the FND of WSN is shown in Figure 6.1. The performance that CPF and CROSS algorithms achieved has a relationship with the values of w while, as expected, LEACH has no relationship. Accordingly, CPF achieved better network lifetime than both algorithms when it has w values: ($w \leq 0.3$ and $w \geq 0.8$). In particular, it achieves longer nodes lifetime when $w = 0.1$ and $d = 0.9$. This is due to the fact that under fewer w and larger d , the nodes get the largest payoff value for collaboration, i.e., the

equilibrium probability will be increasing. As a result, a larger number of nodes will be interested to join C-strategy by analyzing that probability. Then, from available C-strategies, several times the node which has a maximum cooperative-rate has been selected as a CH.

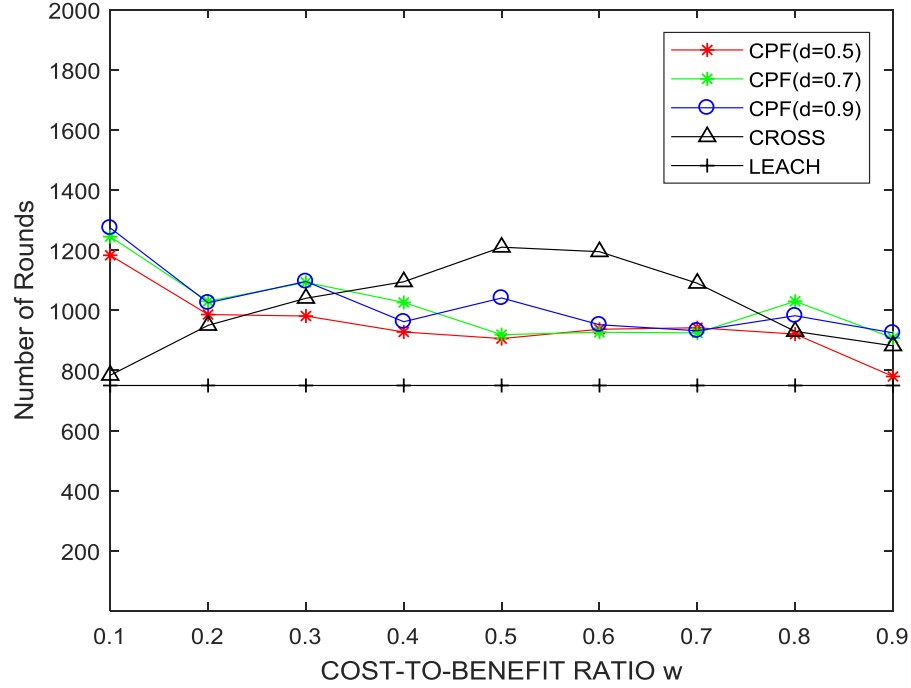


Figure 6.1: The First Node Dead for Different Values of w

As w increases, FND is kept decreasing for both CPF and CROSS. When compared with CROSS the reduction is insignificant in CPF due to the mechanism of rewarding. Thus, unlike CROSS, CPF performs better even though the cost of collaboration has increased. Otherwise, CROSS performs better than both algorithms when it achieved a better collaborative equilibrium, i.e., ($0.3 < w < 0.8$). In this interval, the performance of CPF is between the two algorithms.

Considering the different values of w , the LND for three algorithms is shown in Figure 6.2. It is clearly shown that LEACH achieves better than the two algorithms while the performance of CPF ranked second. This could be for the reason that, when the number of active nodes in the network started to decrease, the cooperative probability of the remaining nodes will get increased for both CPF and CROSS algorithms. This probability will be increasing significantly as more and more number of nodes run out of energy. In this case, both algorithms

begin to consume energy with an increasing rate, resulting in higher energy consumption. Thus, as it has been shown by simulation results, LEACH has achieved better network unstable period comparing it with the other two algorithms.

Even though this is the case, still, the CPF algorithm performs better than CROSS when we consider the numbers of nodes that lastly died. In CPF the number of a CH node is kept balanced even if a larger number of cooperative nodes are present at a current round. In this case, each collaborative node that has not served recently as a CH needs to broadcast and compare its rate of cooperation with its neighboring nodes. Accordingly, only one node that has a larger cooperative-rate has to be determined as a forwarding node, thus, it is a CH.

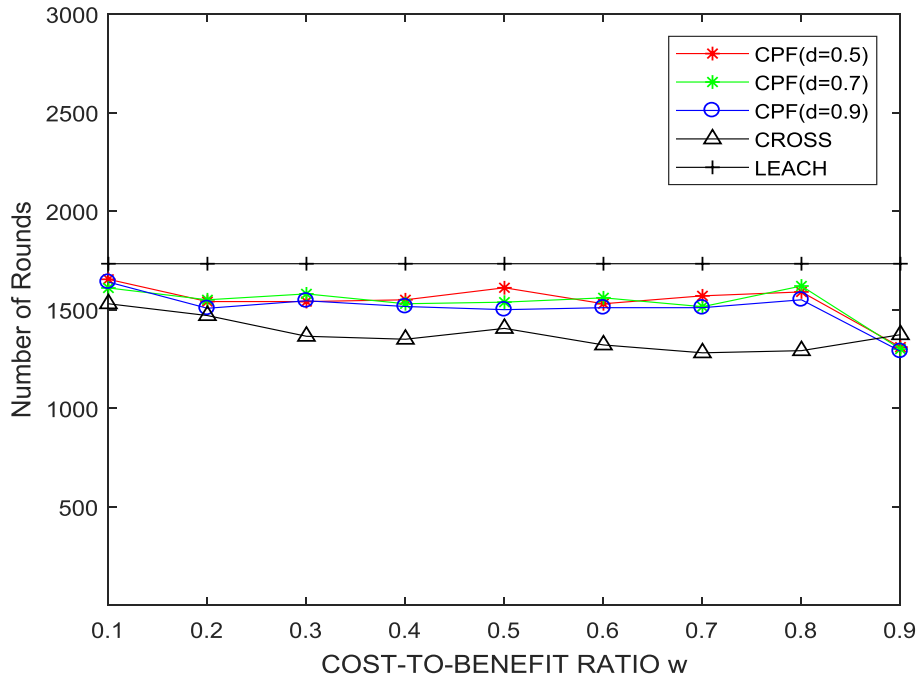


Figure 6.2: The Last Node Dead for Different Values of w

In Figures 6.3a, 6.3b and 6.3c the comparison of LEACH, CROSS and CPF algorithms in terms of the number of nodes that are having positive residual energy with respect to the different values of payoff functions are shown. These represent the distribution of nodes with positive remaining energy in relation to the round of packet transmission. CPF has a large number of nodes with positive remaining energy when it has fewer cost-to-benefit and larger reward-to-benefit ratios. When such proportions are inverted, on the other hand, the number of nodes with

positive remaining energy will be reduced. In this respect, the achieved equilibrium is less, for the reason that the cost of cooperation has been increased. That means some nodes might not hear any of FH announcements. As such, by evaluating their cooperative-rate these nodes bid for FH to transmit packets. In the due courses of such iterations, the CPF consumed much energy power compared to other algorithms.

The distribution of nodes with positive remaining energy is shown in Figure 6.3a for the three algorithms when $d = 0.5$ and w (0.1, 0.5, 0.9). Accordingly, CPF ($w = 0.1$, $d = 0.5$) and CPF ($w = 0.5$, $d = 0.5$) algorithms perform better than LEACH and CROSS, while the algorithm performs less than the two algorithms when $w = 0.9$ and $d = 0.5$.

The CPF ($w = 0.1$, $d = 0.7$) and CPF ($w = 0.5$, $d = 0.7$) algorithms perform better than LEACH and CROSS algorithms, while CPF ($w = 0.9$, $d = 0.7$) performs less than the two algorithms as it has been shown in Figure 6.3b.

In the same manner in Figure 6.3c, CPF ($w = 0.1$, $d = 0.9$) and CPF ($w = 0.5$, $d = 0.9$) perform better than LEACH and CROSS, while CPF ($w = 0.9$, $d = 0.9$) performs less than the two algorithms although the highest reward-to-benefit ratio is provided.

In all of the above cases, as a summary, it is observed that CPF ($w = 0.9$) performs less than LEACH, particularly, starting from the rounds when near to 10% of nodes are dead. This is due to the fact that initially, nodes will not adopt C-strategy as the cost of cooperation is high as well as the number of available nodes are maximum. As a result, in the early deployment phase, many nodes interested to assume Nc-strategy, in which unnecessarily they consume their energy since they bid for FH role repeatedly. Then, later when some nodes start to die and the number of active participants is reduced, the remaining nodes instantly opt to switch to cooperation.

In short, the CPF algorithm has an advantage in achieving collaborative packet communications: resource consumption is well-adjusted between involving nodes by forming a cluster to route packets for members. The role of FH is distributed among these nodes. The FH is also rotated between nodes in the network based on their collaborative scenarios. The energy consumption of this FH has consistently balanced. Thus, the cooperation diversity has been utilized while the network lifetime gets improving.

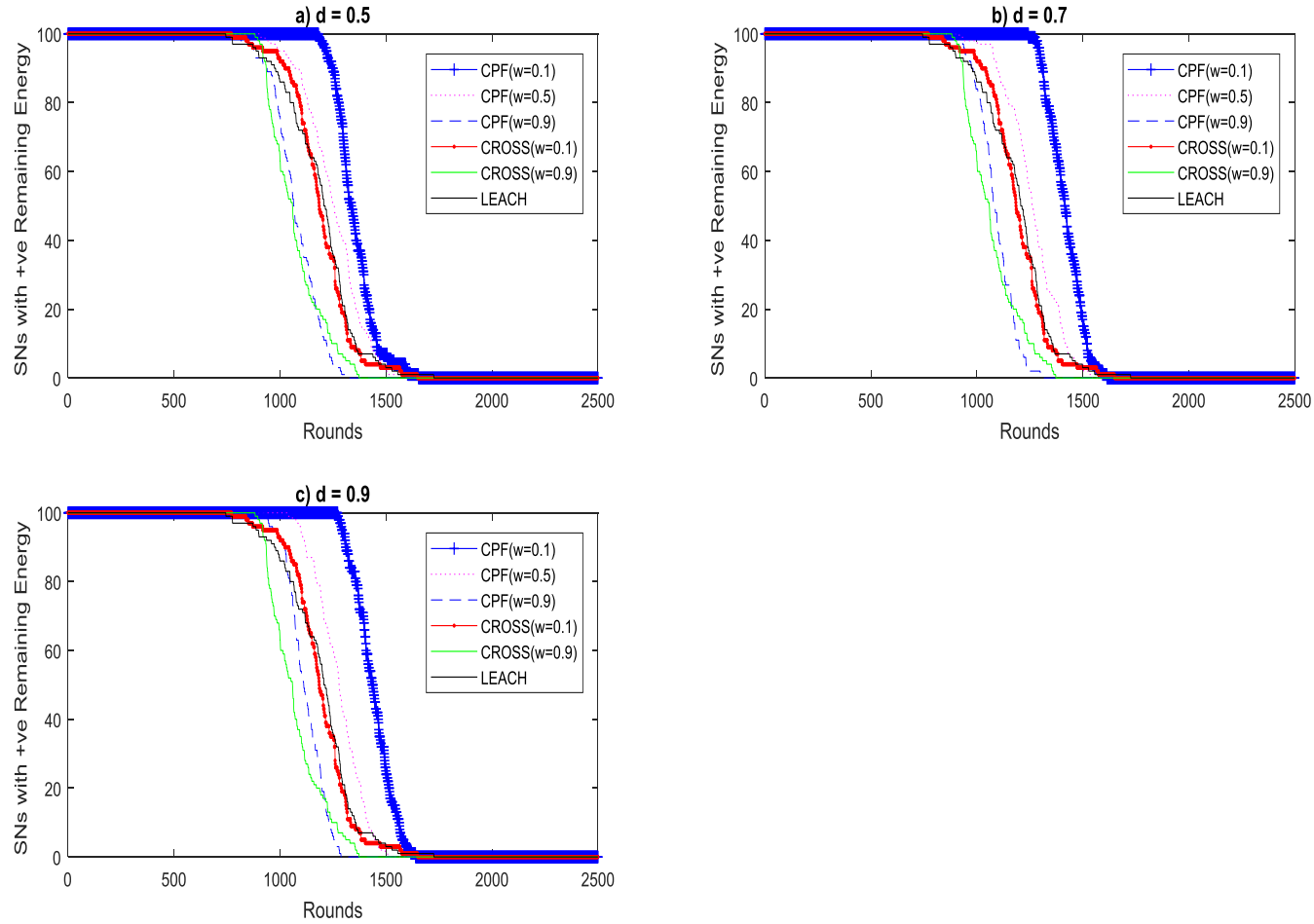


Figure 6.3: The Number of Sensor Nodes with Positive Residual Energy in LEACH, CROSS and CPF Algorithm with Respect to Different Values of Payoff Functions: a) Payoff Parameters, $d = 0.5$ and $w(0.1, 0.5, 0.9)$; b) Payoff Parameters, $d = 0.7$ and $w(0.1, 0.5, 0.9)$; c) Payoff Parameters, $d = 0.9$ and $w(0.1, 0.5, 0.9)$

b) GREET Algorithm

In order to validate the numerical analysis that has been described in Chapter Five, we simulated and assessed the results for GREET routing algorithm. As it has been noted earlier, this algorithm was proposed to overcome the limitations of CPF. As such, the implementation of a fully distributed algorithm has been materialized based on local information. A limited number of collocated nodes interact with their neighboring nodes to reach an evolutionary dynamic equilibrium that passes between them. An interesting result of network lifetime has been obtained and discussed.

According to the results obtained, there is a tradeoff between the performance of GREET algorithm and parameter w . As w increases, i.e., ($w \rightarrow 1$), the equilibrium probability of candidate CHs decreases. In this case, selfish nodes tend to wait for some other nodes to perform the task of sending packets on their behalf. Selfish nodes do not want to risk themselves by sending packets to the BS. When no node is disposed to be a candidate CH, then less number of actual CHs exists in the surrounding network. In this case, each sensor consumes much communication energy for switching into direct communication. As a result, the network lifetime of GREET routing algorithm is reduced as w increases, which is also the case for CPF and CROSS algorithms.

The relation of FND for LEACH, CROSS, CPF, and GREET is shown in Figure 6.4 for varying values of w . Notice that in LEACH, the FND is not a function of the parameter w ; on the contrary, it depends on w in CROSS, CPF, and GREET. With respect to this metrics, it is apparent that GREET outperforms those three algorithms. This happens because, in GREET, the key factor that determines the role of CH is the residual energy of nodes. The node having less residual energy has to be exempted from a CH-determination. As such, the role of CH is fairly rotated between every member node. That makes GREET better than the other algorithms in terms of balancing the energy consumption among nodes. Thus, the network stays for a longer time period to provide a stable functionality.

On the other hand, the other algorithms are unable to consider a node with critical energy in CH selection process. It is observed that the procedure of CH selection is based on a probabilistic way in such algorithms. Accordingly, there is the possibility that ‘hot-spot’ node (i.e., a node which has a minimum energy level) is selected as a CH. Such a selection could be made

regardless of whether the current node has a very low energy level or not. Then, a set of other nodes which are located nearest to such a CH node are likely to join it. That means they become members by sending their gathered data to this CH. In due course, the current CH depletes its energy while trying to perform the role of CH. In this scenario, this node will be soon exhausted. The key technical problem of these algorithms (CPF, CROSS, and LEACH) may be that they cannot solve the tradeoff between prolonging the lifetime for individual nodes and that for the entire sensor networks.

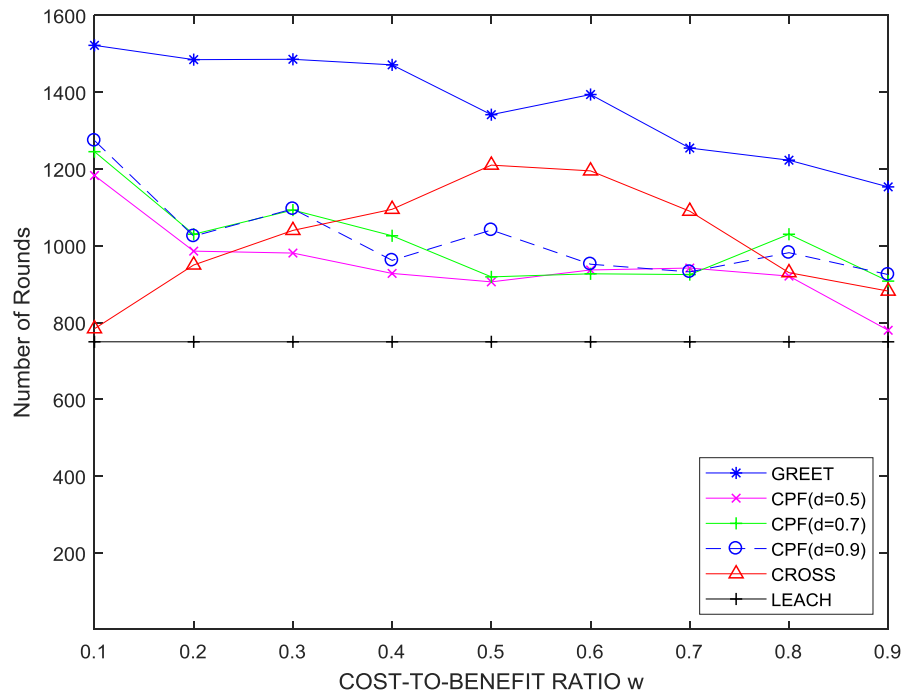


Figure 6.4: The First Node Dead for Different Values of w

The LND for LEACH, CROSS, CPF, and GREET is shown in Figure 6.5 for different values of w . Again GREET outperforms the other algorithms. An interesting observation is the following: GREET achieves a maximum LND for a value around $w = 0.4$, i.e., approximately where the simplified cluster game of the previous chapter was reaching an equilibrium state.

For smaller values of w , LND decreases, since the average number of candidate CHs per round has increased. In other words, the smaller the cost-to-benefit ratio of being a CH, the higher the number of nodes bidding for the CH role, and thus the higher the expected number of

appointed-CHs per round. Otherwise, some of the currently message broadcasted candidates have to rollback into the normal state in which their energy has unnecessary been consumed.

Conversely, for larger values of w , LND degrades i.e., fewer nodes are willing to be a candidate CH (though that might be changed later when the number of active nodes started decreases). In such cases, nodes have to communicate directly with the BS since they have been loner nodes (or some nodes might have acted as selfish), thus, reducing their lifetime. All nodes being CHs and no node being CH is the same as in both cases nodes established direct communication with the BS.

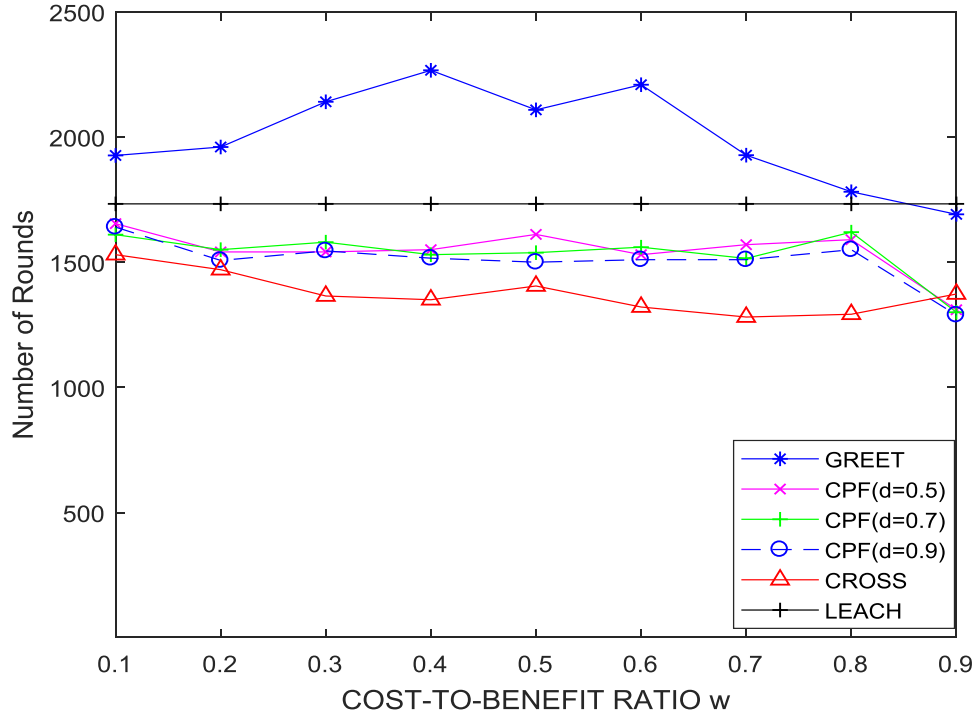


Figure 6.5: The Last Node Dead for Different Values of w

On the other hand, while in LEACH the LND has no relation with w , LND of CROSS, CPF and GREET decreases as the values of w increases. As such, at around $w = 0.9$, LEACH overtakes the other algorithms in terms of LND. As it has been already noted, in those algorithms, the probability of cooperation will decrease when nodes are unwilling to share their resources. Thus, non-cooperative nodes refuse to be CHs or to forward the packets to others.

Figure 6.6 shows the algorithms' performance in terms of the number of nodes with some residual energy. It measures the total number of nodes still alive, which is evaluated at each transmission round. As for the equilibrium probability in the cluster game, GREET has the highest energy saving around $w = 0.4$. Obviously, the energy expenditure rate of GREET is more balanced than that of LEACH, CROSS, and CPF, since CH has been determined in accordance with the node's residual energy. Nodes that have recently served as a CH also stay in the CH-disallowed state until their residual energy is almost the same as that of their neighbors. Moreover, the actual CHs are approximately uniformly distributed over the whole area, because every CH is at least R_{contest} meters away from any others. Consequently, the energy usage of all nodes would be more efficient.

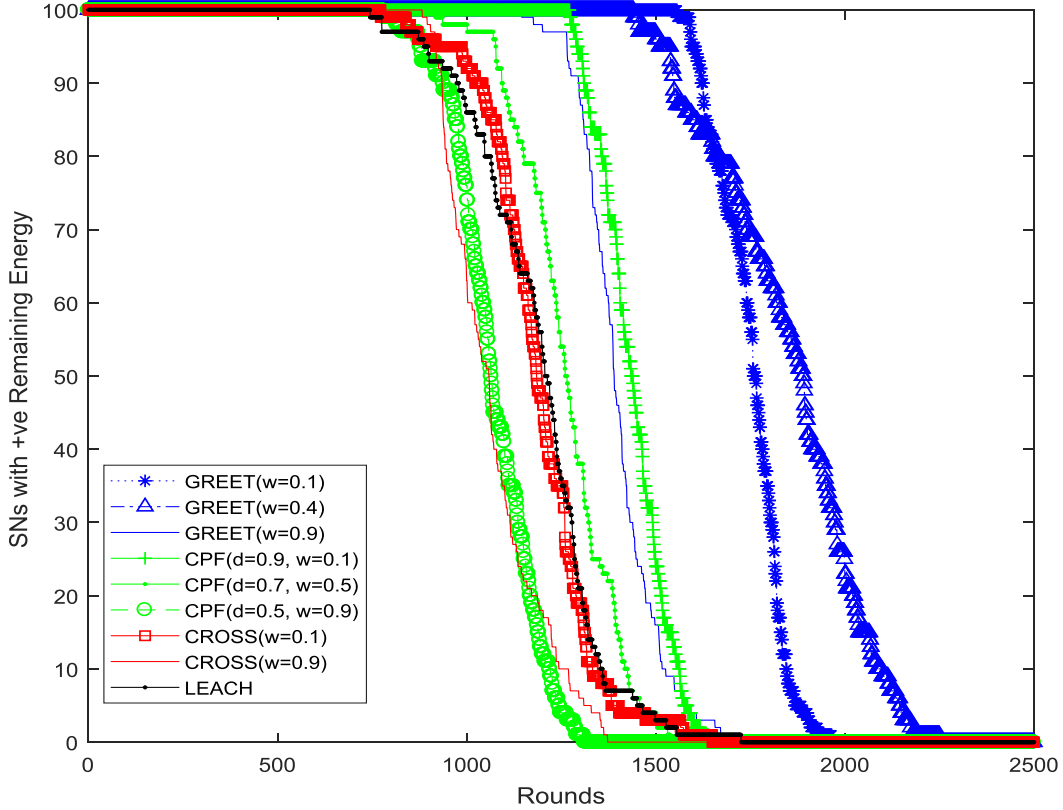


Figure 6.6: The Number of Nodes with Positive Residual Power

In contrast, the technique of energy balancing is not adopted into other algorithms (i.e., LEACH, CROSS, and CPF). In such algorithms, a CH node is assigned in a random mechanism regardless of node's current energy performance. It makes the distribution of CH

non-uniform. Therefore, unbalanced energy consumption appears to be the case. In this regard, certain nodes deplete their energy while the other nodes remain relatively intact (these nodes have ample energy).

Lastly, as shown in Figure 6.7, the average number of data packets sent to the BS has been used for evaluation. The number of CHs determines the amount of data received by the BS since the data collected by member nodes can be received by the BS via the CHs. Both for the values of $w = 0.1$ and $w = 0.4$, GREET has a higher throughput than the other three algorithms. This happens because around the former value, GREET has achieved better FND, while around the latter value, it has achieved effective collaboration. That is, the data packets sensed by every node will be effectively expected to reach the BS.

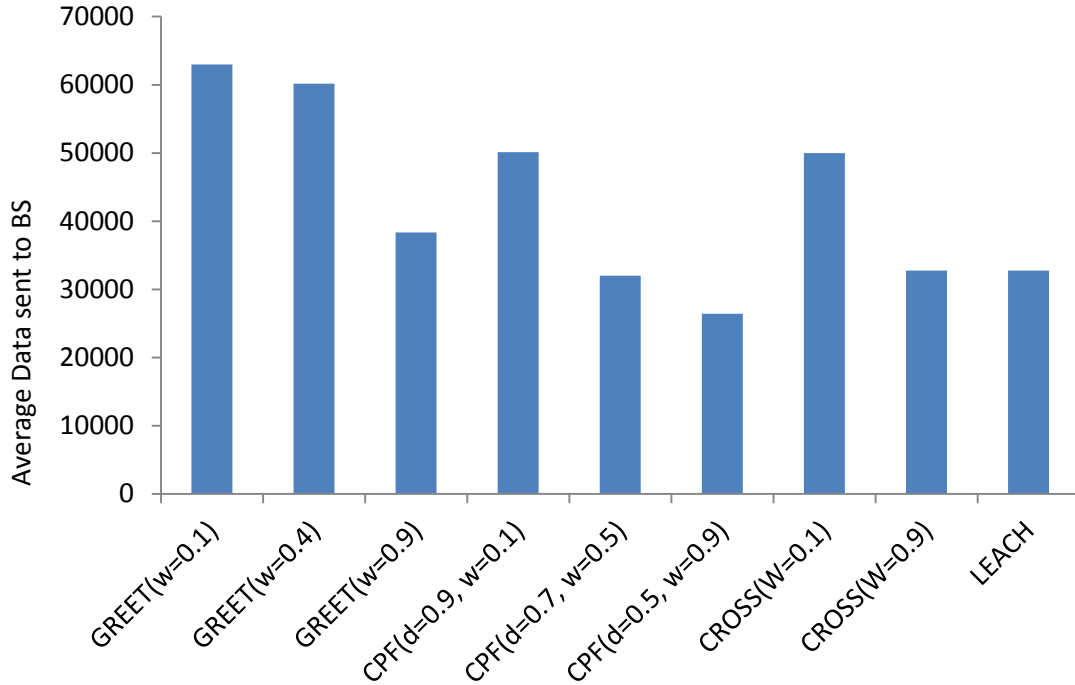


Figure 6.7: Average data sent to the BS (number of packets)

From this standpoint, when the values of $w = 0.1$, CROSS and CPF with $d = 0.9$ also deliver better packet throughput than in LEACH. In LEACH, selfish nodes do not relay the received packets to other nodes and also such nodes may not act as CHs even when required to do so. Moreover, honest nodes' energy is exploited by selfish nodes and hence honest nodes die early. As a result, around the values of $w = 0.9$, GREET features a lower throughput due to the

highest cost of collaboration: selfish nodes do not forward the other nodes' packets; it has also been the case for CPF and CROSS when the value of w increased.

6.4 Summary

In this chapter, simulation analysis has been conducted with respect to evaluating and assessing the performance of algorithms. Their performance results are compared with CROSS and LEACH algorithms using network lifetime or FND, LND, and residual energy.

The comparison of CPF and GREET shows that CPF performs less than GREET in all aspects in the above analysis. It is due to an obvious reason that a larger communication distance consumes much more energy, and results in the early death of some nodes in CPF. In such interactions, nodes are simultaneously playing evolutionary population game, which makes the number of nodes very large. As a result, a node has an extremely small equilibrium probability to play C-strategy which is also the case in the CROSS algorithm. In both algorithms, nodes also unnecessarily consume their communication bandwidth resources. This might further increase the rate of packet collision among the nodes, which might increase energy consumption as a result of attempting a retransmission.

In CPF, for the purpose of increasing the number of collaborators, a mechanism of rewarding is also introduced. However, as a matter of fact, executing and storing the rewarding payoff is expensive and sometimes inapplicable even. That means to compute the rewarding factor itself, nodes consume extra resources (for instance, memory and energy); thus, it is unattainable.

The simulation results show that GREET outperforms the other routing algorithms (CPF, CROSS, and LEACH) in terms of network evaluation metrics namely FND, LND and residual energy). For the reason that the whole process of clustering is locally operated in GREET. In such local operations, nodes conserve their communication energies. Nodes play an evolutionary game with their neighbors to achieve local equilibrium. In such condition, a small set of neighboring nodes interact and bid for candidate CH. Then, a potential candidate CH announces itself to represent its member nodes in routing packets. As a result, the computational and operational cost of selecting a CH is relatively reduced in comparison with algorithms such as CROSS. CPF and CROSS consumed much more energy on transmission because of the larger communication range. This brings in more interference; thus, network lifetime is significantly limited in such algorithms.

In addition, techniques such as local distribution and CH rotation are considered in designing GREET to balance the CH workload among the individual nodes. Selected CH nodes are uniformly distributed in the network since they are R_{contest} meters away from one another. In such range, a node that is having a maximum remaining energy would be determined as a current CH. Then, in the next round, this node is excused from the competition of CH-determination by comparing its remaining energy capacity with its surrounding nodes. In due process, the role of CH is fairly rotated between every node. According to such distributions, other ordinary nodes join their nearest CH, in which the workload is balanced among the current CH nodes. Thus, GREET efficiently balances energy utilization among nodes compared to the other three algorithms. The obtained results from our simulation studies show that GREET remarkably extends network lifetime. Thus, unlike the other algorithms, it can significantly contribute to delivering better network services.

CHAPTER SEVEN: CONCLUSION AND FUTURE WORKS

This chapter concludes the dissertation by summarizing the major contributions made in terms of research challenges; finally, the possible future works will be presented.

7.1 Conclusion

Since sensor nodes are resource-constrained, this raises concerns in their communication. In this regard, they may prefer not to cooperate in packet routing with other non-allied nodes. Such nodes are selfish agents that are targeting to maximize their own utilities (such as energy power) while they are uncooperative in sharing their resources. In this consideration, the network is unable to fully provide user expectation functionalities since its performance is affected. Thus, achieving mutual network operations between these nodes, in the context of designing collaborative routing scheme, is still challenging. In the course of this study, we realized such a problem which required a solution.

In this dissertation, we designed a model that regulates the behaviors of misbehaving nodes that is followed by developing resource-efficient cluster-based routing algorithms. Thus, by using an EGT framework, we defined an ECG model: a system that is consisting of a well-mixed N -nodes population where a node competes with other $N - 1$ nodes. In this model, by considering the node as a player, we studied both pairwise and multi-players competitive game. Nodes contest with each other in the population game by playing a strategy of either C or N_c that experience certain payoff in the course of transmitting packets. As such, replicator dynamics has been adopted for the purpose of strategic guidance, in which a population of nodes evolves and reaches an equilibrium state. These nodes adjust their strategy dynamically towards collaboration by analyzing their benefits and other nodes relative shares.

The bounded rationality of nodes and their limited interaction capabilities with respect to their resources have been considered during model development. From this perspective, the idea of using the theory of an evolutionary game over the other theories is given more emphasis. An evolutionary process is also characterized by the evolutionarily stable state, which outlines that every node must share its resources so as to receive a better payoff. It is also a distributed model, whereby the percentage of nodes shares the information by themselves independently. Hence, the model gives special attention to conserve nodes' resource.

The equilibrium behaviors such as stable and unstable (nodes play either C or Nc strategy) have been identified. For that reason, with respect to the dynamic behavior of non-collaborative nodes, the system should evolve toward a stable state, where individual nodes reach an agreement of not turning away from in order to achieve a better network performance. Thus, the equilibrium strategy of nodes' cooperation should be selected and adopted dynamically. A rewarding mechanism was also analyzed, with the objective of fostering collaboration where a very large number of nodes' contest in a game.

With this in mind, the emergence of structured equilibrium was analyzed both in theoretical and numerical terms. The theoretical analysis used a mathematical computation for a small number of nodes while numerical simulations have been conducted for a very large number of nodes. The results show that the level of collaborative equilibrium probability $x_C^{(*)}$ decreases with the growth of w and N . During these states, a large number of nodes preferred to change their strategies into non-cooperative. On the other hand, the number of collaborators increases when larger rewards are introduced. In this regard, the numerical simulation data are in good agreement with the result of what is theoretically analyzed.

Further, to investigate the quality of the model in real scenarios, cluster-based routing algorithms were proposed. First, we proposed a CPF algorithm which is later extended into a localized GREET development. In CPF, we studied a model of sensor networks based on the introduced incentives. We observed that the system evolved based on replicator dynamics to reach a global collaborative equilibrium. Then, nodes considered for implementing this equilibrium behavior in the development of CPF algorithm. Furthermore, we developed the NcPF algorithm when nodes cannot reach a common collaboration. We compared the two algorithms by simulation, in which CPF algorithm is able to extend the nodes' energy utilization.

In the development of GREET algorithm, neighboring nodes interact and form a cluster game. They autonomously decide what strategy to adapt to get a better benefit. By continuously adopting the stable equilibrium that is locally reached between them, these nodes receive a better benefit in the networks. Over time, potential nodes are determined through a process of natural adaptation to represent their member nodes in the ecosystem. Determining the role of CH at a local level and rotating between nodes according to their current energy level are some

of the techniques that are adopted. Such a determined node is a CH, and it executes the packet routing operations. As such, the correctness and fairness of localized CH selection are further guaranteed so as to preserve the lifetime of nodes with little remaining energy.

Finally, the performance evaluations of our algorithms have been conducted through simulations. As such, the network lifetime and the residual energy along with the packet throughput have been assessed (i.e., our algorithms have been compared with LEACH and CROSS). The CPF better extends network lifetime when compared with LEACH and CROSS. Further, the conducted simulations have confirmed that the GREET algorithm outperforms the other algorithms in terms of energy utilization and network lifetime to provide better throughput.

In conclusion, there are many cases where our algorithm (viz. GREET) can be applied in the realities of sensor networks. In certain remote area sensor network applications, the network is left unattended to perform monitoring and reporting once deployed. Many proposed environmental sensing applications are also grouped under this category. Thus, rather than enforcing collaborative behavior, we introduced an evolutionary mechanism which regulates the behaviors of nodes. Accordingly, our mechanism guides every node toward adapting strategic stable equilibrium in mutual packet routing.

7.2 Summary of Our Contributions

We have presented an achievement of evolutionary collaborative equilibrium as a mechanism of regulating the behaviors of non-cooperative nodes. Accordingly, we have proposed a novel cluster-based routing algorithm that extends the functional lifetime of the network. Thus, our major contributions can be summarized as follows:

ECG: We have proposed a mechanism of modeling and regulating the strategies of non-cooperative nodes in designing an algorithm. It has been developed by using an EGT approach where every node plays an evolutionary dynamics by adopting either C or Nc strategy while receiving payoffs. The advantage of EGT model is that it is more realistic than those postulating full rationality: it counts upon the use of little computation by the node, and assume observations as the basis for decisions.

The equilibrium probability has been derived for the population according to the replicator dynamics: the nature that can model by capturing the adaptation of nodes' strategy change over round, and reaches a stable state. Accordingly, the developed model evolves toward stable equilibrium with respect to the dynamic behavior of such nodes. In any case, a node adopts mechanisms such as adaptive learning with the objective of updating its strategies. As such, the node switches into a more successful strategy in the evolutionary game in order to survive its communication resources (such as energy utilization). The achievement of collaborative equilibrium is also presented both theoretically and numerically using simulation analyses. Our simulation results are in good qualitative agreement with the replicator dynamics results.

In short, in ECG analytical model, we assumed that the interactions of nodes establish either a population game or a cluster game. In the former, the whole nodes interact and share the global information while in the latter nodes interact at a local level. In both cases, however, nodes receive certain payoffs and adjust their future strategies in the developments of mutual routing. Thus, in the model development, the payoff functions have been dynamically analyzed by sensor nodes in order to stay in a stable state once they are reached. The rewarding mechanism has been introduced into the population game in order to improve the equilibrium probability achievements. In this respect, the mutual collaborative goal is achieved when individually-owned nodes reach a common agreement.

The amended model called cluster game has been applied to balance the energy consumptions between neighbors, (limited number of nodes' interactions) by locally achieving evolutionary stable equilibrium without the enforcement of any external mechanisms. The advantages of locally computed analytic model are twofold: (1) dividing big sensor networks into small sized sub-networks with a small number of nodes, (2) GREET algorithm uses parallel processing which is done in each cluster. Nodes are also considered to be independent players that are only concerned with local knowledge. Put it in another way, individual nodes only need local information rather than the global knowledge of the whole network for the execution of this dynamic evolution. In this respect, sensor node verifies is a utility function with its neighbors in order to update its strategy. Thus, in such cases of limited network coverage, the model is employed to balance communication resources.

We point out that the structure of this game is rather general and applies to many contexts in the real world, where the costs of an achievement are shared by the contributors only, while the benefits of the achievement are shared among contributors and non-contributors alike.

CPF Cluster-Based Routing Algorithm: We have proposed a CPF algorithm with the main objective of analyzing the behaviors of nodes in real scenarios. The default case otherwise called NcPF algorithm is evaluated in the case of the nodes that are unwilling to cooperate, and its result is compared with that of CPF. In cluster-based CPF algorithm, misbehaving nodes globally start adopting incentive-based collaborative equilibrium. The performances of the two algorithms are compared when nodes have better positive remaining energy under cluster-based CPF algorithm than when they are under NcPF algorithm. Even if the CPF has some deficiency in managing nodes' resources, its simulation results have achieved better network lifetime when compared with LEACH and CROSS algorithms. So, our proposed cluster-based CPF algorithm has important features in sustaining network functionalities.

GREET Cluster-Based Routing Algorithm: We proposed localized, energy-efficient and distributed algorithm. GREET is encouraged by an evolutionary approach when nodes randomly engage and reach stable strategy with their neighbors. In such a context, it is implemented according to the local dynamic equilibrium which can be achieved and shared between nodes across their R_{contest} . By so doing, GREET has enormous contributions with respect to regulating the behaviors of resource-limited nodes.

The proposed algorithm sustained the lifetime of energy critical node by incorporating two-level energy balancing processes. First, such node would not be allowed to return back to CH-enabled state when starting any new rounds. It would be excused to stay in CH-disallowed until its remaining energy is not less than its neighbors. Second, in the case of presented candidate CHs that are more than two in the same range, only one with maximum residual energy would be allowed to serve an actual CH. In addition, energy consumed by the CH can be balanced using the techniques of local CH distribution and by rotating the CH workload. CH is determined at every R_{contest} meters so as to make the distribution fairly uniform. Similarly, the workload of CH rotates between nodes. The rotation has been done according to the utility of every node which is computed based on residual energies and equilibrium probabilities. Thus,

our algorithm conserves energy by rotating and adjusting the appropriate nodes for CH role. Effectively, it also balances energy among the currently determined CHs.

Further, the algorithm is distributed to help the entire nodes autonomously in forming a local cluster. In contrary, any central station is not required to control or to broadcast information at every round. According to the conducted analysis, GREET also executes in low message control. Furthermore, the computational and operational cost of CH-determination has relatively been minimized when compared with the other algorithms namely CROSS, and CORE. Larger communication ranges of such algorithms waste much more energy in the course of transmission, which is able to bring more interference.

Extending the lifetime of individually-owned node that forms MWSNs is the advantage that our algorithm provides. Thus, unlike CROSS and LEACH, GREET can adapt well to the non-cooperative nodes to be able to provide to a better packet throughput. In this respective, it significantly utilizes the diversity between such network agencies. Our algorithm has effectively been performed by establishing an evolutionary collaborative equilibrium in packet transmission amongst the differently-owned nodes; and to make sure that nodes accept and forward the packets that are produced by another one, on a reciprocity basis. In this regard, they can increase the network lifetime globally as well as their own locally.

7.3 Future Works

In recent years, there has been a considerable amount of research in the area of sensor network applications aimed at optimizing the communication resources. The trend shows that a small size sensor node is becoming a natural part of the future development of computer networking. As such, the smarter sensor node should be considered as the possible implementation of the connection of everything in the world. Thus, the integration of sensor network structures will be increasingly diversified in our surroundings. Nodes in such networks may or may not agree in routing the packets for one another. In such cases, to sustain the sensor network operations overall, collaborative cluster-based routing algorithms such as GREET will be considered. Accordingly, this algorithm will be assimilated into the network layer of sensor networks to route the packet efficiently.

Some of the visualized future works that can be considered as a continuation of this work are listed as follows:

Nodes Grouping in Agencies: In the ECG model, we adopted the worst case scenario, in which each node belongs to a different network. This has been analyzed numerically in order to incorporate our model into the designing and implementation of GREET algorithm. The model with a finite number of selfish agencies each owning more than one sensor node is discussed in Section 5.4.3. Its simulative study with respect to incorporating into GREET algorithm will be the term of our future works. In addition, the future studies focus on the designing of network topologies as well as the applications, where the BS might not be shared by selfish agencies. To this end, our development target is extending our current work into a cluster routing algorithm where the BS might not be shared (i.e., each selfish agency has got separate BS).

Heterogeneous Nodes: There are two kinds of clustering schemes on the basis of energy: when nodes have same initial energy, the scheme is said to be homogeneous while it is said heterogeneous when they have different initial energies of deployment. In the current development, the homogeneities of nodes (differ only in position and remaining energy level) have been considered. In the future study, we will incorporate the heterogeneities of differently interconnected network entities. Thus, the evolutionary dynamics game we proposed in this dissertation will be easily extended to the players of nodes with heterogeneous (see also [50]). Accordingly, by extending the feature of GREET algorithm, one can develop the evolutionary model that studies the behaviors of heterogeneous entities. In line with this, the dynamics and ESSs properties of the game would be analyzed for their implementation.

Repetitive Cluster Set-up: When more than two candidate CHs contest in the same sensing region, the determined actual CH will be a candidate node which has a better residual energy. The other candidate CHs have to return back to the normal state after receiving an actual CH announcement. Then, once the currently appointed CH serves, the algorithm will start a fresh phase of the round to determine another candidate (i.e., a new set-up phase again). In such scenarios, the repetitious processes of cluster set-up will consume much energy.

Minimizing such iterations will be one way to reduce such broadcasting overhead. Accordingly, to improve this weakness, our future works will incorporate certain mechanisms of scheduling. Thus, the currently announced candidate of CHs will get turn-by-turn the chance to serve the other nodes as an actual CH. That means, candidate CHs will avoid the state of returning to the normal because they need to compete for the actual CH role in the next round.

By so doing, the iteration of cluster set-up will be reduced. In this respect, the extended work, therefore, reduces message broadcasting overhead.

Multi-hop Communication: Most of the contributions made by GREET algorithm focused on the cluster set-up stage. In this setting, the duple communication ranges is considered for designing GREET algorithm: nodes can disseminate data either in short-range R_{contest} or long-range L_{contest} mode. Nodes utilize the L_{contest} energy consumption when they are actual CHs to send packets to the BS; on the other hand, they consumed the R_{contest} one for the remaining activities. In due process, nodes conserve their transmission energy by switching between R_{contest} and L_{contest} power amplification.

There is still much space to improve the lifespan of individual nodes, which will further advance the performance of data transmission. A multi-hop communication is a mainstream technique for such large-scale MWSNs, in which it conserves the energy of nodes. Thus, the single-hop concept of GREET algorithm will be enhanced to multi-hop (CH-to-CH) communication by considering an energy-efficient technique.

Security and Privacy: Securing the data packets in collaborative routing is essential in MWSNs. According to this context, due to the collaboration of differently-owned nodes, the intercommunication schemes of such networks face security challenges in the form of privacy, integrity, and confidentiality. The collaborative cluster routing needs to protect the security of the sensed information. These intercommunication resources should be protected from unauthorized entities. For instance, in the case when the sensed information is user's personal information, such sensitive information has to be protected. The collaborative cluster routing needs to keep the integrity of the sensed information.

Such collaborative design will have the necessity of additional security and confidentiality mechanisms which certainly lead to extra energy overheads. Thus, to extend the lifetime of the sensor network, the security-related problems arising from such design are worth of studying.

BIBLIOGRAPHY

- [1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer Networks*, Vol. 38, No. 4, pp. 393–422, 2002.
- [2] I. F. Akyildiz and I. H. Kasimoglu, "Wireless sensor and actor networks: Research challenges," *Ad Hoc Networks*, Vol. 2, No. 4, pp. 351–367, 2004.
- [3] K. Akkaya and M. Younis, "A survey on routing protocols for wireless sensor networks," *Ad Hoc Networks*, Vol. 3, No. 3, pp. 325–349, 2005.
- [4] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey," *Computer Networks*, Vol. 52, No. 12, pp. 2292–2330, 2008.
- [5] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient Communication Protocol for Wireless Microsensor Networks," in *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*, 2000, pp. 3005–3014.
- [6] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An Application-Specific Protocol Architecture for Wireless Microsensor Networks," *IEEE Transactions on Wireless Communications*, Vol. 1, No. 4, pp. 660–670, 2002.
- [7] S. Naeimi, H. Ghafghazi, C. O. Chow, and H. Ishii, "A Survey on the Taxonomy of Cluster-Based Routing Protocols for Homogeneous Wireless Sensor Networks," *Sensors (Switzerland)*, Vol. 12, No. 6, pp. 7350–7409, 2012.
- [8] M. Aslam, N. Javaid, A. Rahim, U. Nazir, A. Bibi, and Z. A. Khan, "Survey of Extended LEACH-Based Clustering Routing Protocols for Wireless Sensor Networks," in *IEEE 14th International Conference on High Performance Computing and Communication and 2012 IEEE 9th International Conference on Embedded Software and Systems*, 2012, pp. 1232–1238.
- [9] S. Lmdsey and C. S. Raghavendra, "PEGASIS: Power-Efficient Gathering in Sensor Information Systems," in *Aerospace conference proceedings*, Vol. 3, pp. 3–3, 2002.
- [10] S. D. Muruganathan, D. C. F. Ma, R. I. Bhasin, and A. O. Fapojuwo, "A Centralized

- Energy-Efficient Routing Protocol for Wireless Sensor Networks,” IEEE Communications Magazine, Vol. 43, No. 3, pp. S8-13, 2005.
- [11] G. Lee, M. Lee, W. Seok, J. Kwak, and O. Byeon, “A Base Station Centralized Simple Clustering Protocol for Sensor Networks,” International Federation for Information Processing (IFIP) 2006, pp. 628–637, 2006.
- [12] M. Chatterjee, S. Das, and D. Turgut, “WCA: A Weighted Clustering Algorithm for Mobile Ad Hoc Networks,” Cluster Computing, pp. 193–204, 2002.
- [13] C. H. Lin and M. J. Tsai, “HEED: A Hybrid, Energy-Efficient, Distributed clustering approach for Ad Hoc Sensor Networks,” IEEE Transactions on Mobile Computing, Vol. 5, No. 10, pp. 1471–1472, 2006.
- [14] G. Koltsidas, F.-N. Pavlidou, and G. K. F. Pavlidou, “A Game Theoretical Approach to Clustering of Ad-Hoc and Sensor Networks,” Telecommunication Systems, Vol. 47, No. 1–2, pp. 81–93, 2010.
- [15] D. Xie, Q. Sun, Q. Zhou, Y. Qiu, and X. Yuan, “An efficient clustering protocol for wireless sensor networks based on localized game theoretical approach,” International Journal of Distributed Sensor Networks, Vol. 2013, 2013.
- [16] S. Salim, X. Li, and S. Moh, “Cost- and Reward-Based Clustering for Wireless Sensor Networks: A Performance Tradeoff,” in Wireless and Optical Communication Conference (WOCC), 2013, pp. 421–425.
- [17] A. Rogers and N. R. Jennings, “Selfish Sensors in Wireless Micro-Sensor Networks,” in Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems, 2004, pp. 1320–1321.
- [18] M. Felegyhazi, J.-P. Hubaux, and L. Buttyan, “Cooperative Packet Forwarding in Multi-Domain Sensor Networks,” Third IEEE International Conference on Pervasive Computing and Communications Workshops, pp. 345–349, 2005.
- [19] L. Buttyan, T. Holczer, and P. Schaffer, “Spontaneous Cooperation in Multi-Domain Sensor Networks,” in Proceedings of 2005 2nd European Workshop on Security and Privacy in Ad-Hoc and Sensor Networks, 2005, pp. 42–53.

- [20] G. V Crosby and N. Pissinou, "Evolution of Cooperation in Multi-Class Wireless Sensor Networks," in *Proceedings - Conference on Local Computer Networks (LCN)*, 2007, pp. 793–798.
- [21] M. J. Shamani, H. Gharaee, S. Sadri, and F. Rezaei, "Adaptive energy aware cooperation strategy in heterogeneous multi-domain sensor networks," *Procedia Computer Science*, Vol. 19, pp. 1047–1052, 2013.
- [22] F. Garcin, M. H. Manshaei, and J. Hubaux, "Cooperation in Underwater Sensor Networks," *Sensors (Peterborough, NH)*, pp. 540–548, 2009.
- [23] S. Yokoyama, Y. Nakane, O. Takahashi, E. Miyamoto, E. Mi, and S. Nodes, "Evaluation of the Impact of Selfish Nodes in Ad Hoc Networks and Detection and Countermeasure Methods," in *Proceedings - IEEE International Conference on Mobile Data Management*, 2006.
- [24] S. Gupta, C. K. Nagpal, and Charu Singla, "Impact of Selfish Node Concentration in MANETs," *International Journal of Wireless and Mobile Networks*, Vol. 3, No. 2, pp. 29–37, 2011.
- [25] R. Juliana and P. U. Mahenwari, "Performance Degradation of Heterogeneous Wireless Sensor Network in the Presence of Non Cooperative Nodes," *International Journal of Computer Science and Telecommunications*, Vol. 4, No. 4, 2013.
- [26] M. Dua, S. Gupta, B. Bhushan, and C. K. Nagpal, "Performance Evaluation of Routing Protocol with Selfish Users in Realistic Environment," *International Journal of Modern Education and Computer Science*, Vol. 5, No. 6, pp. 49–55, 2013.
- [27] K. Bicakci and B. Tavli, "Prolonging network lifetime with multi-domain cooperation strategies in wireless sensor networks," *Ad Hoc Networks*, Vol. 8, No. 6, pp. 582–596, 2010.
- [28] N. Nisan, T. Roughgarden, E. Tardos, and V. V. Vazirani, *Algorithmic Game Theory*, First Edit. 32 Avenue of the Americas, New York, NY, USA: Cambridge University Press, 2007.
- [29] G. Szabó and G. Fáth, "Evolutionary games on graphs," *Physics Reports*, Vol. 446, No.

- 4, pp. 97–216, 2007.
- [30] L. Kockesen and E. A.OK, An Introduction to Game Theory. New York University, 2007.
- [31] R. Axelrod and D. Dion, “The Further Evolution of Cooperation,” American Association for the Advancement of Science, Vol. 242, No. 4884, pp. 1385–1390, 1988.
- [32] J. Maynard Smith, “Evolution and the Theory of Games,” in Cambridge University Press, 1982.
- [33] J. Maynard Smith and G. R. Price, “The Logic of Animal Conflict,” Nature, Vol. 246, pp. 15–18, 1973.
- [34] R. Axelrod, The Evolution of Cooperation. Printed in the United States of America: Basic Books, Inc., New York, 1984.
- [35] S. Ganeriwalt, S. Ganeriwalt, I. Aad, I. Aad, J. Hubaux, and J. Hubaux, “On Selfish Behavior in CSMAKA Networks,” in Traffic, 2005, pp. 2513–2524.
- [36] M. Yan, L. Xiao, L. Du, and L. Huang, “On selfish behavior in wireless sensor networks: A game theoretic case study,” in Proceedings - 3rd International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), 2011, Vol. 2, pp. 752–756.
- [37] D. Levin, “Punishment in Selfish Wireless Networks : A Game Theoretic Analysis,” Proceedings of Economics of Networked Systems, 2006.
- [38] S. M. Priya, K. T. K. Rama, A. Jeevarathinam, and K. Lakshmi, “A Novel approach for identifying greedy nodes in wireless sensor network by using EEGN algorithm,” International Journal on Computer Science and Engineering (IJCSE), Vol. 2, No. 9, pp. 2928–2931, 2010.
- [39] S. Marti, T. J. Giuli, K. Lai, and M. Baker, “Mitigating routing misbehavior in mobile ad hoc networks,” in Proceedings - 6th annual international conference on Mobile computing and networking MobiCom '00, 2000, Vol. 1, No. 18, pp. 255–265.
- [40] L. Huang and L. Liu, “Extended Watchdog Mechanism for Wireless Sensor Networks,” Journal of Information and Computing Science, Vol. 3, No. 1, pp. 39–48, 2008.

- [41] P. Chhillar, Smita, and Sunita, "Detection of Greedy Nodes over Wireless Sensor Networks," *International Journal of Engineering Sciences and Research Technology*, Vol. 2, No. 4, pp. 2–5, 2013.
- [42] J. G and R. Dorai D, "Ranking Wireless Sensor Networks," *The International Journal of Engineering and Science (IJES)*, Vol. 3, No. 1, pp. 52–55, 2014.
- [43] X. Lin et al., "Utility-Based Node Cooperation Mechanism in Wireless Sensor Networks," *International Journal Communications, Network and System Sciences (IJCNS)*, Vol. 6, pp. 236–243, 2013.
- [44] F. Bao, I.-R. Chen, M. Chang, and J.-H. Cho, "Hierarchical Trust Management for Wireless Sensor Networks and Its Application to Trust-Based Routing," in *Proceedings of the 2011 ACM Symposium on Applied Computing*, 2011, pp. 1732–1738.
- [45] H. C. Leligou et al., "The Impact of Indirect Trust Information Exchange on Network Performance and Energy Consumption in Wireless Sensor Networks," in *Proceedings Elmar- International Symposium Electronics in Marine*, 2011, pp. 153–156.
- [46] V. Srinivasan, P. Nuggehalli, C. F. Chiasserini, and R. R. Rao, "Energy Efficiency of Ad Hoc Wireless Networks with Selfish Users," in *European Wireless Conference*, 2002.
- [47] L. Buttyan and J. Hubaux, "Nuglets : a Virtual Currency to Stimulate Cooperation in Self-Organized Mobile Ad Hoc Networks," *Swiss Federal Institute of Thnology, Lausanne*, 2001.
- [48] L. Buttyán and J. P. Hubaux, "Enforcing service availability in mobile ad-hoc WANs," in *1st Annual Workshop on Mobile and Ad Hoc Networking and Computing, MobiHOC 2000*, 2000, pp. 87–96.
- [49] L. Buttyan and J. Hubaux, "Stimulating Cooperation in Self-Organizing Mobile Ad Hoc Networks," *ACM/Kluwer Mobile Networks and Applications*, Vol. 8, No. 5, 2003.
- [50] A. Barreira da Silva Rocha, A. Laruelle, and P. Zuazo, "Replicator Dynamics and Evolutionary Stable Strategies in Heterogeneous Games," *Working Paper No. 11/54*, *Leiceste University, Dept. of Economics*, 2011.
- [51] P. D. Taylor and L. B. Jonker, "Evolutionarily Stable Strategies and Game Dynamics,"

- Journal of Mathematical Biosciences, Vol. 16, pp. 76–83, 1978.
- [52] P. T. Sivasankar and M. Ramakrishnan, “Invulnerable Cluster Head Election Model to Handle Selfishness in Wireless Sensor Network,” *Research Journal of Applied Sciences, Engineering and Technology*, Vol. 9, No. 2, pp. 79–83, 2015.
- [53] S. Shen, G. Yue, Q. Cao, and F. Yu, “A Survey of Game Theory in Wireless Sensor Networks Security,” *Journal of Networks*, Vol. 6, No. 3, pp. 521–532, 2011.
- [54] P. Bisht and A. Kumar, “Selfishness of Discriminate Node in Caching Based Wireless Sensor Network,” *International Journal of Advanced Research in Computer Engineering and Technology (IJARCET)*, Vol. 2, No. 2, pp. 582–586, 2013.
- [55] A. Agah, S. K. Das, and K. Basu, “A Game Theory based Approach Security in Wireless Sensor Networks,” in *Proc.IEEE International Conference on Performance, Computing, and Communications*, 2004, pp. 259–263.
- [56] A. Agah and S. K. Das, “Preventing DoS attacks in wireless sensor networks: A repeated game theory approach,” *International Journal of Network Security*, Vol. 5, No. 2, pp. 145–153, 2007.
- [57] Y. B. Reddy, “A Game Theory Approach to Detect Malicious Nodes in Wireless Sensor Networks,” in *Sensor Technologies and Applications, SENSORCOMM '09,Third International Conference on*, 2009, pp. 462–468.
- [58] W. Wang, M. Chatterjee, and K. Kwiat, “Coexistence with malicious nodes: A game theoretic approach,” in *Proceedings of the 2009 International Conference on Game Theory for Networks, GameNets '09*, 2009, pp. 277–286.
- [59] S. Arora, P. Singh, and A. J. Gupta, “Adaptive Selection of Cryptographic Protocols in Wireless Sensor Networks using Evolutionary Game Theory,” in *Procedia Computer Science*, page 78, pp.358-366.
- [60] L. Tan, S. Zhang, and J. Qi, “Cooperative Cluster Head Selection Based on Cost Sharing Game for Energy-efficient Wireless Sensor Networks,” *Journal of Computational Information Systems*, Vol. 9, No. 8, pp. 3623–3633, 2012.
- [61] H. Jing and H. Aida, “A cooperative game theoretic approach to clustering algorithms

- for wireless sensor networks,” in 2009 IEEE Pacific Rim Conference on Communications, Computers and Signal Processing, 2009, pp. 140–145.
- [62] M. Afsar, “Energy-Efficient Coalition Formation in Sensor Networks: a Game-Theoretic Approach,” arXiv preprint arXiv:1512.08019, 2015.
- [63] Z. Xu, Y. Yin, X. Chen, and J. Wang, “A Game-theory Based Clustering Approach for Wireless Sensor Networks,” in the 2nd International Conference on Next Generation Computer and Information Technology, 2013, Vol. 27, pp. 58–66.
- [64] M. Feldman, L. Lewin-Eytan, and J. (Seffi) Naor, “Hedonic clustering games,” in Proceedings of the 24th ACM symposium on Parallelism in algorithms and architectures - SPAA '12, 2012, pp. 267–276.
- [65] Z. Xu, Y. Yin, and J. Wang, “An Density-based Energy-efficient Routing Algorithm in Wireless Sensor Networks Using Game Theory,” International Journal of Future Generation Communication and Networking, Vol. 5, No. 4, pp. 99–112, 2012.
- [66] C. Lin, G. Wu, M. Li, X. Chen, Z. Liu, and L. Yao, “A selfish node preventive real time fault tolerant routing protocol for WSNs,” in 2011 IEEE International Conferences on Internet of Things, and Cyber, Physical and Social Computing, iThings/CPSCoM 2011 Int. Conf. and 4th Int. Conf. Cyber, 2011, pp. 330–337.
- [67] Z. Zeng-Wei, W. Zhao-hui, and L. Huai-zhong, “Clustering Routing Algorithm Using Game-Theoretic Techniques for WSNs,” in Proceedings of 2004 IEEE International Symposium on Circuits and Systems, 2004, Vol. 4, pp. IV-904–7.
- [68] J. Wang, Z. Chen, Deng, and Xiao-heng, “A Trustworthy Energy-Efficient Routing Algorithm Based on Game-Theory for WSN,” in Wireless Mobile and Computing (CCWMC 2009), International Communication Conference (IET) on, 2009, pp. 192–196.
- [69] L. Sun, H. Sun, B. Yang, and G. Xu, “A repeated game theoretical approach for clustering in mobile ad hoc networks,” in 2011 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), 2011, pp. 1–6.
- [70] L. Lin, Z. Xianwei, D. Yu, D. Liping, and M. Zhonggui, “Differential Game Based

- Centralized Clustering Algorithm for Wireless Sensor,” in 2009 First International Conference on Future Information Networks, 2009.
- [71] D. Lee, H. Shin, and C. Lee, “Game theory-based resource allocation strategy for clustering based wireless sensor network,” in Proceedings of the 6th International Conference on Ubiquitous Information Management and Communication (ICUIMC) ’12, 2012.
- [72] A. Jangra, Swati, Richa, and Priyanka, “Wireless Sensor Network (WSN): Architectural Design Issues and Challenges,” (IJCSE) International Journal on Computer Science and Engineering, Vol. 2, No. 9, pp. 3089–3094, 2010.
- [73] W. Wang and Y. Wang, “Truthful Multicast in Selfish Wireless Networks,” Network, 2004.
- [74] W. Wang, M. Chatterjee, and K. Kwiat, “Cooperation in Wireless Networks with Unreliable Channels,” in IEEE Transactions on Communications, 2011, Vol. 59, No. 10, pp. 2808–2817.
- [75] Vikram Srinivasan, Pavan Nuggehalli, C. F. Chiasserini, and R. R. Rao, “Cooperation in Wireless Ad Hoc Networks,” in IEEE INFOCOM 2003, Twenty-second Annual Joint Conference of the IEEE Computer and Communications Societies (IEEE Cat. No.03CH37428), 2003, pp. 808–817.
- [76] V. Srivastava et al., “Using game theory to analyze wireless ad hoc networks,” IEEE Communications Surveys and Tutorials, Vol. 7, No. 1–4, pp. 46–56, 2005.
- [77] S. Eidenbenz, G. Resta, and P. Santi, “The COMMIT protocol for truthful and cost-efficient routing in ad hoc networks with selfish nodes,” IEEE Transactions on Mobile Computing, Vol. 7, No. 1, pp. 19–32, 2008.
- [78] R. . Biradar and V. Patil, “Classification and comparison of routing protocols in wireless sensor networks,” Special Issue on Ubiquitous Computing Security Systems, Vol. 4, No. 1, pp. 704–711, 2009.
- [79] M. Rubinstein, I. Moraes, and M. Campista, “A survey on wireless ad hoc networks,” Networks, pp. 1–33, 2006.

- [80] S. P. Singh and S. C. Sharma, "A survey on cluster based routing protocols in wireless sensor networks," *Procedia Computer Science*, Vol. 45, pp. 687–695, 2015.
- [81] K.Ramesh and K.Somasundaram, "A Comparative Study of Cluster Head Selection Algorithms in Wireless Sensor Networks," *International Journal of Computer Science and Engineering Survey (IJCSES)*, Vol. 2, No. 4, 2011.
- [82] A. Sarrafi, M. H. Firooz, and M. Kamarei, "A Hybrid Algorithm for Topology Optimization in Wireless Sensor Networks," in *2006 International Conference on Software in Telecommunications and Computer Networks*, 2006, pp. 121–126.
- [83] D. Bhattacharyya, T. Kim, and S. Pal, "A Comparative Study of Wireless Sensor Networks and Their Routing Protocols," *Sensors*, Vol. 10, No. 12, pp. 10506–10523, 2010.
- [84] K. C. Rahman, "A Survey On Sensor Network," *Journal of Computer and Information Technology*, Vol. 1, No. 1, pp. 76–87, 2010.
- [85] S. Sukumaran, V. J, and Arunkorath, "A Survey of Methods to mitigate Selfishness in Mobile Ad hoc Networks," *International Journal of Information and Communication Technology Research*, Vol. 1, No. 2, pp. 73–80, 2011.
- [86] V. Jolly and S. Latifi, "Comprehensive Study of Routing Management in Wireless Sensor Networks- Part-1," in *ICWN*, 2006, pp. 37–44.
- [87] A. Azim and M. M. Islam, "Deterministic cluster head selection for wireless sensor networks," in *2012 25th IEEE Canadian Conference on Electrical and Computer Engineering: Vision for a Greener Future, CCECE 2012*, 2012.
- [88] W. Rungworawut, T. Senivongse, and K. Cox, "An Energy-Efficient Clustering Using a Round-Robin Method in a Wireless Sensor Network," in *Proceedings - SERA 2007: Fifth ACIS International Conference on Software Engineering Research, Management, and Applications*, 2007, pp. 409–416.
- [89] Zamini, M. Samad, and L. Zare, "A Reward based method to wireless sensor network clustering," in *Application of Information and Communication Technologies (AICT), International Conference on. IEEE*, 2009.

- [90] H. Khamfroush, "Lifetime Increase for Wireless Sensor Networks Using Cluster-Based Routing," in International Association of Computer Science and Information Technology - Spring Conference (IACSIT-SC), 2009, pp. 14–18.
- [91] H. Chen, C. S. Wu, Y. S. Chu, C. C. Cheng, and L. K. Tsai, "Energy Residue Aware (ERA) clustering algorithm for LEACH-based wireless sensor networks," Second International Conference on Systems and Networks Communications (ICSNC), 2007.
- [92] A. K. Paul, M. Tariq, Y. Li, and T. Sato, "EECS: An Energy Efficient Clustering Scheme in Wireless Sensor Networks," in Proceedings of the 24th IEEE International Performance, Computing, and Communications Conference (IPCCC), 2005, pp. 535–540.
- [93] T. El-fouly, A. Abdaoui, and R. D. Rile, "A Survey of Game-Theoretic Methodology in Wireless Sensor Network Routing," Procedia Computer Science, 2012. pp. 1–5.
- [94] S. V. J. E, P. Ganeshkumar, V. S. G, M. Sultan, and D. Kaleeswaran, "A Survey on Algorithms for Cluster Head Selection in WSN," International Journal of Advanced Research in Computer Engineering and Technology (IJARCET), Vol. 2, No. 5, pp. 1909–1913, 2013.
- [95] G. Chen, C. Li, M. Ye, and J. Wu, "An unequal cluster-based routing protocol in wireless sensor networks," Wireless Networks, Vol. 15, No. 2, pp. 193–207, 2009.
- [96] A. P. Jyothi, "Trends and Technologies used for Mitigating Energy Efficiency Issues in Wireless Sensor Network," International Journal of Computer Applications, Vol. 111, No. 3, pp. 32–40, 2015.
- [97] C. Cheng, C. K. Tse, F. C. M. Lau, and S. Member, "A Clustering Algorithm of Cluster-head Optimization for Wireless Sensor Networks Based on Energy," Journal of Information and Computational Science, Vol. 11, No. 8, pp. 2129–2136, 2011.
- [98] D. Mahmood, N. Javaid, S. Mahmood, S. Qureshi, A. M. Memon, and T. Zaman, "MODLEACH: A variant of LEACH for WSNs," in Proceedings - 2013 8th International Conference on Broadband, Wireless Computing, Communication and Applications (BWCCA), 2013, pp. 158–163.

- [99] W.-D. Wang, "A Hierarchical Clustering Algorithm and Cooperation Analysis for Wireless Sensor Networks," *Journal of Software*, Vol. 147, No. 5, pp. 1157, 2006, 1157-
- [100] R. Machado and S. Tekinay, "A survey of game-theoretic approaches in wireless sensor networks," *Computer Networks*, Vol. 52, No. 16, pp. 3047–3061, 2008.
- [101] H.-Y. H. Shi, W. W.-L. Wang, N.-M. N. Kwok, and S. S.-Y. Chen, "Game theory for wireless sensor networks: A survey," *Sensors* 2012, Vol. 12, No. 7, pp. 9055–9097, 2012.
- [102] S. Midha, A. K. Sharma, and G. Sikka, "A Survey on Wireless Sensor Network Clustering Protocols Optimized via Game Theory," *ACM SIGBED Review*, Vol. 11, No. 3, pp. 8–18, 2014.
- [103] L. Tan, S. Zhang, and J. Qi, "An Intelligent Cooperative Protocol in Clustered Wireless Sensor Networks for Energy-Efficiency," *Journal of Computational Information Systems*, Vol. 8, No. 4, pp. 1415–1423, 2012.
- [104] Z. Ishaq, S. Park, and Y. Yoo, "A security framework for Cluster-based Wireless Sensor Networks against the selfishness problem," in *International Conference on Ubiquitous and Future Networks (ICUFN)*, 2015, pp. 7–12.
- [105] G. V. Crosby and N. Pissinou, "Cluster-based Reputation and Trust for Wireless Sensor Networks," in *Consumer Communications and Networking Conference (CCNC) 4th IEEE*, 2007, pp. 604–608.
- [106] L. Selvaraj and Tamizharasan P., "A Reliable Trust System for Cluster in Wireless Sensor Network," *International Journal of Innovative Science, Engineering and Technology (IJISSET)*, Vol. 1, No. 3, pp. 325–329, 2014.
- [107] A. K. Tripathy and S. Chinara, "Comparison of Residual Energy-Based Clustering Algorithms for Wireless Sensor Network," *International Scholarly Research Network, ISRN Sensor Networks*, Vol. 2012, pp. 1–10, 2012.
- [108] S. Singh and Meenaxi, "A Survey on Energy Efficient Routing in Wireless Sensor Networks," *International Journal of Advanced Research in Computer Science and Software Engineering (IJARCSSE)*, Vol. 3, No. 7, pp. 200–205, 2013.

- [109] B. Priya and S. S. Manohar, "Lifetime Enhancement of Cluster Based Wireless Sensor Network through Energy Efficient MAC Protocol," *Circuits and Systems*, Vol. 7, pp. 2296–2308, 2016.
- [110] C.-L. Fok, C. Julien, G.-C. Roman, and C. Lu, "Challenges of Satisfying Multiple Stakeholders: Quality of Service in the Internet of Things," in *Proceeding of the 2nd workshop on Software Engineering for SEnsor Network Applications (SESENA) '11*, 2012, pp. 55–60.
- [111] C. Alcaraz, P. Najera, J. Lopez, and R. Roman, "Wireless Sensor Networks and the Internet of Things: Do We Need a Complete Integration?" *1st International Workshop on the Security of the Internet of Things (SecIoT'10)*, 2010.
- [112] A. Behzadan, A. Anpalagan, and B. Ma, "Prolonging Network Lifetime via Nodal Energy Balancing in Heterogeneous Wireless Sensor Networks," in *IEEE Communications Society, IEEE ICC 2011 proceedings*, 2011.
- [113] T. Himsoon, W. P. Siri Wongpairat, Z. Han, and K. J. R. Liu, "Lifetime Maximization by Cooperative Nodes and Relay Deployment in Wireless Sensor Networks," in *IEEE Journal on Selected Areas in Communications*, 2007, Vol. 25, No. 2, pp. 306–316.
- [114] A. Schillings and K. Yang, "A Collaborative and Energy Efficient Data Routing Algorithm for Wireless Sensor Networks Through the Use of Game Theory," in *London Communications Symposium (LCS) '06.*, 2006, pp. 93–96.
- [115] S. Sergi and G. M. Vitetta, "A Game Theoretical Approach to Distributed Relay Selection in Randomized Cooperation," *IEEE Transactions on Wireless Communications*, Vol. 9, No. 8, pp. 2611–2621, 2010.
- [116] J. Von Neumann and O. Morgenstern, *Theory of games and economic behavior*. Princeton: Princeton University Press, 1944.
- [117] J. F. Nash, "Equilibrium Points in n-Person Games," in *Proceedings of the National Academy of Sciences of the United States of America*, 1950, Vol. 36, No. 1, pp. 48–49.
- [118] J. Miekisz, "Evolutionary game theory and population dynamics," *arXiv*, 2007.
- [119] K. Sigmund, "Introduction to evolutionary game theory," in *Proceedings of Symposia in*

- Applied Mathematics, 2011, Vol. 69, pp. 1–25.
- [120] D.-F. Zheng, H. Yin, C. Chan, and P. M. Hui, “Cooperative Behavior in a Model of Evolutionary Snowdrift Games with N -person Interactions,” *Physica A* 387, pp. 23–26, 2008.
- [121] M. O. Souza, J. M. Pacheco, and F. C. Santos, “Evolution of Cooperation under N-person Snowdrift Games,” *Journal of Theoretical Biology*, Vol. 260, No. 4, pp. 581–588, 2009.
- [122] X. Yao and P. Darwen, “An Experimental Study of N-Person Prisoner’s Dilemma Games,” *Progress in Evolutionary Computation*, Vol. 18, pp. 90–108, 1994.
- [123] M. Ji, C. Xu, D. F. Zheng, and P. M. Hui, “Enhanced cooperation and harmonious population in an evolutionary N-person snowdrift game,” *Physica A: Statistical Mechanics and its Applications*, Vol. 389, No. 5, pp. 1071–1076, 2010.
- [124] J. A. G. Moreira, “Evolutionary Dynamics of Cooperation in Multiplayer Games,” PhD Dissertation, Universidade De Lisboa, 2011.
- [125] R. Kümmerli, C. Colliard, N. Fiechter, B. Petitpierre, A. Russier, Flavien, and L. Keller, “Human cooperation in social dilemmas: comparing the Snowdrift game with the Prisoner’s Dilemma,” *Physorg.com*, pp. 1–2, 2007.
- [126] R. Chiong and M. Kirley, “Iterated N-player games on small-world networks,” *Genetic and Evolutionary Computation Conference (GECCO)’11*, pp. 1123–1130, 2011.
- [127] B. Wang, K. J. R. Liu, and T. C. Clancy, “Evolutionary Cooperative Spectrum Sensing Games: How to Collaborate?,” *IEEE transactions on communications*, Vol. 58, No. 3, pp. 890–900, 2010.
- [128] B. Wang, K. J. R. Liu, and T. C. Clancy, “Evolutionary game framework for behavior dynamics in cooperative spectrum sensing,” in *GLOBECOM - IEEE Global Telecommunications Conference*, 2008, pp. 3123–3127.
- [129] D. E. Charilas and A. D. Panagopoulos, “A survey on game theory applications in wireless networks,” *Computer Networks*, Vol. 54, No. 18, pp. 3421–3430, 2010.
- [130] M. Zheng, “Game theory used for reliable routing modeling in Wireless Sensor

- Networks,” *Parallel and Distributed Computing, Applications and Technologies, PDCAT Proceedings*, pp. 280–284, 2010.
- [131] E. Karapistoli and A. Economides, “Routing in Wireless Sensor Networks: An approach using Stackelberg games,” in *7th International Workshop on Selected Topics in Mobile and Wireless Computing Routing*, 2014, pp. 322–327.
- [132] R. Kannan, C. Busch, and A. Vasilakos, “Quality of Routing Congestion Games in Wireless Sensor Networks,” in *Proceedings of the Fourth International Wireless Internet Conference*, 2008.
- [133] B. Arisian and K. Eshghi, “A game theory approach for optimal routing: In wireless sensor networks,” *6th International Conference on Wireless Communications Networking and Mobile Computing (WiCOM)*, 2010.
- [134] R. Valli and P. Dananjayan, “A Non-Cooperative Game Theoretical Approach for Power Control in Virtual MIMO Wireless Sensor Network,” *International Journal of UbiComp (IJU)*, Vol. 1, No. 3, 2010.
- [135] H. Ren, M. Q. H. Meng, and L. Xu, “Conflict and coalition models in inhomogeneous power allocation for wireless sensor networks,” in *2008 IEEE International Conference on Robotics and Biomimetics, ROBIO 2008*, 2008, pp. 2056–2060.
- [136] Y. Zhu, Y. Xu, L. Liu, and S. Qiu, “A Power Control Algorithm Based on Non-cooperative Game for Wireless CDMA Sensor Networks,” *International Conference on Computational and Information Sciences*, Vol. 4, No. 2, pp. 718–721, 2011.
- [137] R. Kannan, S. Wei, V. Chakravarthy, and G. Seetharaman, “Using misbehavior to analyze strategic versus aggregate energy minimization in wireless sensor networks,” *International Journal of Distributed Sensor Networks*, Vol. 2, No. 3, pp. 225–249, 2006.
- [138] X. Chu and H. Sethu, “Cooperative Topology Control with Adaptation for improved lifetime in wireless sensor networks,” *Ad Hoc Networks*, Vol. 30, pp. 99–114, 2015.
- [139] C. Pau, A. Pages-Zamora, and J. Fernandez-Rubio, “A Game Theoretical Algorithm for Joint Power and Topology Control in Distributed WSN,” *International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, IEEE, 2009, pp. 2765–2768.

- [140] E. Campos-Nañez, A. Garcia, and C. Li, “A Game Theoretic Approach to Efficient Power Management in Sensor Networks,” *Operations Research*, pp. 1–30, 2008.
- [141] S. I. Nayer and H. H. Ali, “Dynamic Energy Aware Gur Game based Algorithms for Self Optimizing Wireless Sensor Networks,” *Self-Organizing Systems*, Vol. 4, No. 3, pp. 776–787, 2013.
- [142] R. S. Komali and A. B. MacKenzie, “Distributed topology control in ad-hoc networks: a game theoretic perspective,” in *Consumer Communications and Networking Conference (CCNC) 3rd IEEE*, 2006, Vol. 1, pp. 563–568.
- [143] O. Baig, Y. S. Ai-Harhi, and E. Al-Tubaishi, “Game-theoretic algorithm stimulating cooperation in multi-hop wireless networks,” *5th International Conference on Game Theory for Networks, GameNets 2014*, 2014.
- [144] W. Huang and S. Zhang, “Research on the Wireless Sensor Network Management Methodologies based on the Runtime Model and Game Theory,” *International Journal of Future Generation Communication and Networking*, Vol. 9, No. 3, pp. 229–242, 2016.
- [145] E. Altman, R. Elazouzi, Y. Hayel, and H. Tembine, “An Evolutionary Game approach for the design of congestion control protocols in wireless networks,” pp. 547–552, 2008.
- [146] G. Jiang, S. Shen, K. Hu, L. Huang, H. Li, and R. Han, “Evolutionary game-based secrecy rate adaptation in wireless sensor networks,” *Hindawi Publishing Corporation, International Journal of Distributed Sensor Networks*, Vol. 1, No. 11, 2015.
- [147] R. V. Fonseca, “Fault-Tolerant Wireless Sensor Networks using Evolutionary Games,” *PhD Dissertation, The University of New Mexico*, 2012.
- [148] M. A. Abd, B. K. Singh, S. F. Al Rubeai, and K. E. Tepe, “Game Theoretic Energy Balanced (GTEB) Routing Protocol for Wireless Sensor Networks,” in *2014 IEEE Wireless Communications and Networking Conference (WCNC)*, IEEE, 2014, Vol. 3, pp. 2564–2569.
- [149] Y. Zhang, D. Huang, M. Ji, and F. Xie, “The evolution game analysis of clustering for asymmetrical multi-factors in WSNs,” *Computers and Electrical Engineering*, Vol. 39, No. 6, pp. 1746–1757, 2013.

- [150] Z. Chen, Y. Qiu, J. Liu, and L. Xu, "Incentive mechanism for selfish nodes in wireless sensor networks based on evolutionary game," *Computers and Mathematics with Applications*, Vol. 62, No. 9, pp. 3378–3388, 2011.
- [151] H. Tembine, E. Altman, R. El-Azouzi, and Y. Hayel, "Evolutionary games in wireless networks," in *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 2010, Vol. 40, No. 3, pp. 634–646.
- [152] M. A. Khan, H. Tembine, and A. V. Vasilakos, "Game dynamics and cost of learning in heterogeneous 4G networks," *IEEE Journal on Selected Areas in Communications*, Vol. 30, No. 1, pp. 198–213, 2012.
- [153] S. Maharjan, C. Yuen, Y. H. Chew, Y. Zhang, and S. Gjessing, "Distributed spectrum sensing for cognitive radio networks with heterogeneous traffic," in *2010 3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL)*, 2010, No. 1, pp. 1–5.
- [154] C. Jiang, Y. Chen, Y. Gao, and K. J. R. Liu, "Evolutionary Game for Joint Spectrum Sensing and Access in Cognitive Radio Networks," in *Global Communications Conference (GLOBECOM)*, 2013 IEEE, pp. 1113-1118.
- [155] Y. Dai and J. Wu, "Whether and When to Share: Spectrum Sensing as An Evolutionary Game," in *Proceedings of the 8th International Conference on Cognitive Radio Oriented Wireless Networks*, 2013, pp. 1–6.
- [156] S. K. Das, P. S. Chatterjee, and M. Roy, "Detecting and Punishing the Selfish Node and its Behavior in WSN," *Detecting and Punishing the Selfish Node and its Behavior in WSN*, Vol. 6, No. 1, pp. 11–15, 2014.
- [157] B. Chen, J. L. Mao, N. Guo, G. H. Qiao, and N. Dai, "An incentive detection mechanism for cooperation of nodes selfish behavior in wireless sensor networks," in *25th Chinese Control and Decision Conference (CCDC)*, 2013, pp. 4021–4024.
- [158] J. Konorski and R. Orlikowski, "A Framework for Detection of Selfishness in Multihop Mobile Ad Hoc Networks," *Journal of Telecommunications and Information Technology*, 2009.

- [159] D. Aarthy and B. C., “Detecting Selfish Routing and Misbehavior of Malicious Node in Disruption Tolerant Networks,” *International Journal of Emerging Technology and Advanced Engineering*, Vol. 3, No. 1, pp. 285–290, 2013.
- [160] S. Zou, W. Wang, and W. Wang, “A routing algorithm on delay-tolerant of wireless sensor network based on the node selfishness,” *EURASIP Journal on Wireless Communications and Networking*, No. 1, 2013.
- [161] S. Dasgupta and P. Dutta, “A Novel Game Theoretic Approach for Cluster Head Selection in WSN,” *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, Vol. 2, No. 3, pp. 2278–3075, 2013.
- [162] V. Vinoba and S. M. Chithra, “Enhance the Energy Lifetime of Wireless Sensor Networks Using Game Theory,” *International Journal of Electrical and Electronic Engineering and Telecommunications*, Vol. 1, No. 1, 2015.
- [163] Ramakant S. Komali and A. B. MacKenzie, “Effect of selfish node behavior on efficient topology design,” in *IEEE Trans. on Mobile Computing*, 2008.
- [164] L. Clare, G. Pottie, and J. Agre, “Self-organizing distributed sensor networks,” in *Proc. SPIE Conference Unattended Ground Sensor Technologies and Applications*, Vol. 3713, 1999, pp. 229–237.
- [165] F. Sivrikaya and B. Yener, “Time synchronization in sensor networks: a survey,” *IEEE Network*, Vol. 18, No. 4, pp. 45–50, 2004.
- [166] S. G. Foss and S. A. Zuyev, “On a Voronoi Aggregative Process Related to a Bivariate Poisson Process,” *Advances in Applied Probability*, Vol. 28, No. 4, pp. 965–981, 1996.
- [167] A. Gilat, *MATLAB: An Introduction with Applications*, Fourth Edi. Printed in the United States of America: John Wiley and Sons, Inc., 2011.
- [168] Q. I. Ali, “Simulation Framework of Wireless Sensor Network (WSN) Using MATLAB / SIMULINK Software,” in *MATLAB – A Fundamental Tool for Scientific Computing and Engineering Applications-Volume 2*, InTech. Open Science, 2012, pp. 263–284.
- [169] M. Simek and P. Moravek, “Modeling of Energy Consumption of Zigbee Devices in Matlab Tool,” *Elektrorevue*, Vol. 2, No. 3, pp. 41–46, 2011.

- [170] G. A. Di Caro, “Analysis of Simulation Environments for Mobile Ad Hoc Networks,” Technical Report No. IDSIA-24-0326, 2003
- [171] T. Cevik and F. Ozyurt, “Impacts of Structural Factors on Energy Consumption in Cluster based Wireless Sensor Networks: a Comprehensive Analysis,” International Journal of Ad hoc, Sensor and Ubiquitous Computing (IJASUC), Vol. 6, No. 1, pp. 1–19, 2015.
- [172] Z. A. Khan and S. Sampalli, “AZR-LEACH: An Energy Efficient Routing Protocol for Wireless Sensor Networks,” International Journal Communications, Network and System Sciences, Vol. 5, pp. 785–795, 2012.
- [173] A. Amer, A. E. Fawzy, M. Shokair, and W. Saad, “Balanced Energy Efficient Grid based Clustering Protocol for Wireless Sensor Networks,” International Journal of Computing and Digital Systems, Vol. 1, No. 1, 2017.

APPENDIXES

A. The Effect of Selfish Nodes on the Network Performances

Simulation setup: 100 nodes were randomly deployed on the coordination of (400m by 400m) with the respect to the BS located at the center (nodes shared the common BS). The other input parameters have been shown in Table 6.1. The percentages of selfishness were assumed to be fixed (0%, 25%, 50%, and 75%) in the course of deployment.

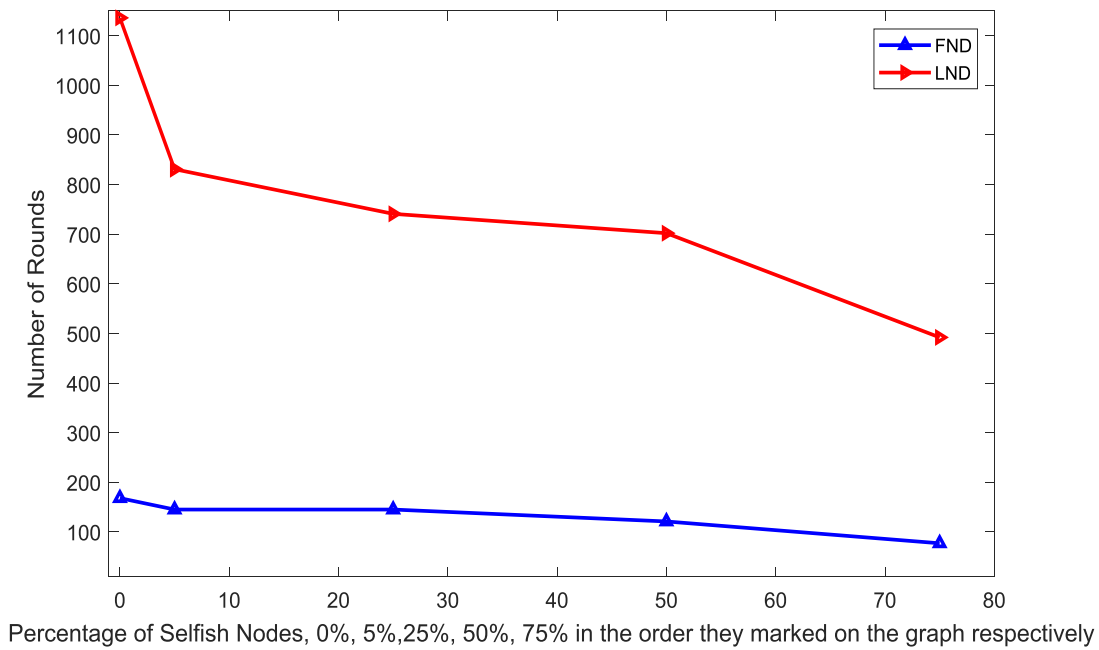


Figure A.1: Network Lifetime as the First and Last Nodes Die

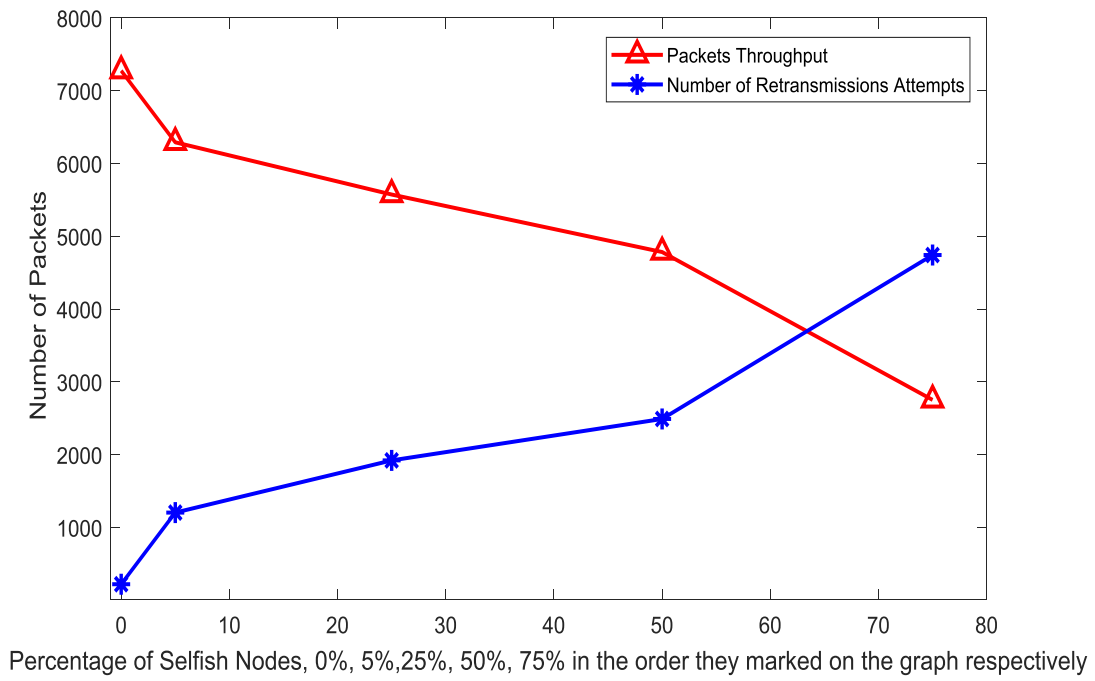


Figure A.2: Packet Throughput and Packet Retransmission Attempts

B. List of Publications

International Journal

K.A. Gameda, G. Gianini, and M. Libsie, “An evolutionary cluster-game approach for Wireless Sensor Networks in non-collaborative settings,” *Pervasive and Mobile Computing* 2017, <https://doi.org/10.1016/j.pmcj.2017.10.008>.

International Conferences

K.A. Gameda, G. Gianini, and M. Libsie, “Collaborative Packets Forwarding to Prolong Network Lifetime in Multi-Class Wireless Sensor Networks,” *I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, 2017 International Conference on. IEEE, 2017.

K.A. Gameda, G. Gianini, and M. Libsie, “The Effect of Node Selfishness on the Performance of WSN Cluster-based Routing Algorithms,” *Proceeding of the 12th IEEE 2015 AFRICON International Conference*, In *AFRICON*, 2015, pp. 1-5, IEEE, 2015.