Distributed traffic estimation and throughput optimization in random access networks

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**DISTRIBUTED TRAFFIC ESTIMATION AND
THROUGHPUT OPTIMIZATION IN RANDOM
ACCESS NETWORKS**

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Abstract

Due to the shared nature of the wireless channel in a random access network, the wireless nodes in a network naturally interact with each other and thus affect the throughput performance and energy consumption of each other. The aim of this thesis is to illustrate the use of local information for the traffic estimation and the throughput optimization in random access networks. Specifically, this thesis investigates various key issues on the design of random access networks, including transmission strategy in a slotted ALOHA network, distributed traffic characterization and throughput optimization in a CSMA network and optimum backoff protocol design in a non-persistent CSMA network.

The traditional use of channel state information (CSI) in a slotted ALOHA network will lead to *Braess Paradox*, i.e., more information resulting in worse throughput performance. This thesis first proposes a new method to exploit the CSI named adaptive CSI method to eliminate the *Braess Paradox* and thus to improve the throughput performance. The use of acknowledgement is explored to estimate the transmission probabilities of other nodes in the network. It thus enables the distributed implementation of the proposed method. Moreover, this research generalizes two simple yet effective guidelines to determine the best transmission strategy under different system scenarios.

Secondly, two novel distributed algorithms are proposed to estimate the on-going traffic in a heterogeneous CSMA network. In contrast to centralized Markov chain models, the proposed methods are able to characterize the traffic without prior information. They are also able to detect changes in the traffic. With the use of the

traffic estimation method, a throughput adjustment algorithm is also proposed to tune the transmission rate of each node with respect to a desired throughput demand.

Finally, the throughput performance of a non-persistent CSMA network under imperfect sensing is thoroughly examined. It is discovered that the traditional binary exponent backoff protocol accounts for the throughput inefficiency in CSMA networks. A novel backoff protocol named probabilistic backoff CSMA (PB-CSMA) is proposed, which is able to achieve optimum throughput performance regardless of the number of nodes as well as the level of sensing errors. Using the clear channel assessment results, the distributed implementation of PB-CSMA is also introduced.

Simulation and experimental studies have been conducted to evaluate the proposed algorithms in terms of accuracy, convergence speed and computational complexity. The results show that with proper use of local information, the traffic intensity can be accurately estimated, the throughput can be significantly improved and the energy consumption can be further reduced for random access networks in a distributed manner.

Contents

Acknowledgement	ii
Abstract	iv
List of Tables	x
List of Figures	xi
List of Abbreviations	xiii
List of Symbols	xiv
1. Introduction	1
1.1 Recent Trends in Wireless Random Access Protocols	1
1.2 Motivations and Objectives	3
1.2.1 Distributed Throughput Optimization in Slotted ALOHA Networks.....	3
1.2.2 Heterogeneous Traffic Estimation in CSMA Networks	4
1.2.3 Throughput Optimization in Heterogeneous CSMA Networks.....	5
1.2.4 Throughput Maximization in CSMA Networks under Imperfect Sensing	6
1.3 Main Contributions	7
1.4 Outline of Thesis.....	9
2. Literature Review	11
2.1 Introduction.....	11
2.2 Transmission Rate Control in ALOHA Networks.....	11
2.3 Modeling of CSMA Networks.....	13
2.4 Exploitation of Local Information and Traffic estimation in CSMA networks	17
2.5 Distributed Optimization using Local Information.....	21
2.6 Summary	25

3. Distributed Transmission Probability Control in Rayleigh-fading ALOHA Networks	27
3.1 Introduction.....	27
3.2 Preliminaries	28
3.2.1 Throughput.....	28
3.2.2 Fading Channel and SINR Capture.....	28
3.2.3 Adaptive CSI-based Transmission Method	29
3.2.4 Acknowledgement Information	30
3.3 Equilibrium Analysis	31
3.3.1 Power Optimization Problem.....	31
3.3.2 Nash Equilibria	31
3.3.3 Existence of Nash Equilibrium	32
3.4 Maximal Throughput Analysis	35
3.5 Power Efficiency Analysis.....	40
3.6 Convergence Analysis	43
3.6.1 ACK-based Game Strategy.....	43
3.6.2 Update Interval Analysis.....	47
3.7 Simulation Results	49
3.8 Summary	54
4. Real-time Distributed Traffic Estimation in CSMA Networks	56
4.1 Introduction.....	56
4.2 Preliminaries and Problem Formulation	57
4.2.1 An Overview of IEEE 802.15.4 CSMA/CA.....	57
4.2.2 Problem Formulation	58
4.3 Markov Chain Channel-State Modeling	60
4.4 Traffic Estimation of CSMA Networks with Constant Packet Length.....	63
4.4.1 Traffic Estimation	63

4.4.2	Detectability Analysis	64
4.5	Traffic Estimation of CSMA Networks with Varying Packet Lengths	69
4.5.1	Traffic Estimation	69
4.5.2	Moving Average Particle Filtering	71
4.6	Simulation Results	75
4.6.1	Results with Constant Packet Length	75
4.6.2	Results with Varying Packet Lengths	77
4.7	Summary	80
5.	Adaptive Throughput Adjustment in CSMA Networks	82
5.1	Introduction.....	82
5.2	Problem Formulation	83
5.3	Distributed Rate Adjustment.....	84
5.4	Change Detection Mechanism	86
5.5	Experimental Results	88
5.6	Summary	95
6.	A Probabilistic Backoff Protocol for Throughput Maximization in a CSMA Network.....	98
6.1	Introduction.....	98
6.2	Preliminaries	99
6.3	Probabilistic Backoff CSMA	100
6.3.1	Operations	100
6.3.2	Markov Chain Modeling.....	101
6.4	Non-Persistent CSMA with Imperfect Sensing	103
6.5	Distributed Probabilistic Backoff Algorithm.....	107
6.5.1	Achievability Analysis.....	107
6.5.2	Distributed Estimation and Tuning.....	108
6.5.3	Sensitivity Analysis	110

6.6	Numerical Results.....	112
6.6.1	Throughput Performance	113
6.6.2	Distributed Algorithm.....	116
6.7	Summary	119
7.	Conclusion and Future Work	120
7.1	Conclusions.....	120
7.2	Future Work	122
7.2.1	Estimation of Hybrid Traffic in Heterogeneous CSMA Networks	122
7.2.2	Comprehensive Use of Local Information.....	122
7.2.3	Co-existence of Different Protocols.....	123
7.2.4	Co-design and Optimization of Wireless Network Control System....	124
	Author's Publications	125
	References	126

List of Tables

Table 3-1 Actual Throughput with Changes on the Number of Nodes.....	53
Table 4-1: The Procedure of ARMA-PF.....	73
Table 4-2 Simulation Settings for Traffic Estimation in CSMA networks.....	74
Table 4-3 Performance Comparisons of Different Tracking Algorithms.....	79
Table 5-1: Pseudo-code of the proposed adjustment algorithm.....	86
Table 5-2 Comparisons of the proposed method and the Markov chain Methods.....	91
Table 6-1: The details of PB-CSMA.....	97
Table 6-2 Parameter Settings of PB-CSMA.....	113

List of Figures

Figure 3-1 Maximum Throughput with Different SNRs (dB) and Capture Ratios	40
Figure 3-2 Throughput Comparison for a Given Transmission Probability $p=0.05$	42
Figure 3-3 Power Reduction for different Power Investment Schemes	43
Figure 3-4 Comparisons between the Simulation Results and the Theoretical Analysis	50
Figure 3-5 Throughput and Transmission Probability for Heterogeneous Networks....	51
Figure 3-6 Performance of the Convergence Algorithm	52
Figure 3-7 Transmission Probability with Changes on the Number of Nodes	53
Figure 4-1 Heterogeneous Channel State Model of an Arbitrary Node i	61
Figure 4-2 Sensitivity with respect to busy channel probability.....	66
Figure 4-3 Minimal detectable aggregate traffic change versus busy channel probability	68
Figure 4-4 Traffic Estimation using (4-9).....	76
Figure 4-5 Traffic Estimation with Different Traffic Types.....	77
Figure 4-6 Autoregressive Moving Average Particle Filter	78
Figure 4-7 Autoregressive Moving Average Filter.....	78
Figure 4-8 Extended Kalman Filter	79
Figure 5-1 The Testing Area.....	89
Figure 5-2 the Floor Plan of the Testing Area	90
Figure 5-3 Experiment results of homogeneous networks	91
Figure 5-4 Experiment results of heterogeneous networks.....	92
Figure 5-5 Busy channel probability in a heterogeneous network with changes on the number of nodes.....	94

Figure 5-6 Actual Throughput in a Heterogeneous Network with changes in the Number	94
Figure 6-1 Markov Chain Model of PB-CSMA	101
Figure 6-2 Normalized Throughput as a Function of Carrier Sensing Probability.....	106
Figure 6-3 Throughput Comparison	113
Figure 6-4 Analytical Throughput of PB-CSMA with Different Levels of Carrier Sensing Errors.....	114
Figure 6-5 Analytical Throughput of PB-CSMA with Different Packet Lengths	115
Figure 6-6 Estimated Number of Active Nodes against Update Interval	117
Figure 6-7 Carrier Sensing Probability against Update Interval.....	117
Figure 6-8 Actual Throughput against Analytical Results	118

List of Abbreviations

ACK	Acknowledgement
ADAPT	ADaptive Access Parameters Tuning Algorithm
ARMA	Autoregressive Moving Average
BCP	Busy Channel Probability
BE	Binary Exponent
CCA	Clear Channel Assessment
CSI	Channel State Information
CSMA	Carrier Sensing Multiple Access
DCF	Distributed Coordination Function
GPRS	General Packet Radio Service
GSM	Global System for Mobile Communications
IoT	Internet of Things
ISM	Industrial, Scientific and Medical
LEAP	Learning-based Tuning Algorithm
MAC	Medium Access Control
NB	Number of Backoffs
PF	Particle Filter
SINR	Signal-to-Interference-and-Noise Ratio
SNR	Signal-to-Noise Ratio
TDMA	Time Division Multiple Access
WLAN	Wireless Local Area Networks
WPAN	Wireless Personal Area Networks

List of Symbols

$\mathbf{Par}$	parameter set in CSMA layer
$E(\mathbf{Par})$	average energy consumption per packet in CSMA networks
$R(\mathbf{Par})$	reliability (packet success rate) in CSMA networks
R_{min}	minimum reliability requirement
$D(\mathbf{Par})$	average delay per packet in CSMA networks
D_{max}	maximum permissible delay
$p_{i,k}$	transmission probability of node i at slot k in ALOHA networks
ρ_i	throughput demand of node i in ALOHA networks
n or N	number of nodes in a network
$SINR_{i,k}$	signal-to-interference-and-noise ratio for node i at time slot k
N	average power of the additive noise at the base station
P_T	the transmission power of each node
$B_{i,k}$	transmission indicator of node i at time slot k
$h_{i,k}$	channel gain between node i and the base station at time slot k
b	radio capture ratio
c_i	tuning factor of the transmission probability
$p_i(c_i)$	average transmission probability of node i in ALOHA networks
p_{PSR}	packet success rate
U_i	utility function of node i in ALOHA networks
r_i	average throughput of node i
r_{t-CSI}	system throughput using the threshold-based CSI method
r_{no-CSI}	system throughput using the no CSI method
r_{a-CSI}	system throughput using the adaptive CSI method
λ_i	transmission rate of node i in CSMA networks
L_i	packet length of node i
β_i	busy channel probability of node i
α_i	channel sensing probability of node i
m	maximum backoff attempts

B_{slot}	number of bits in a time slot in a CSMA network
θ_i	packet success rate of node i in a CSMA network
$\mathbf{z}_i$	local information set of node i in a CSMA network
B	number of CCA in an update interval
D	number of ACK in an update interval
C_k	busy channel indicator during update interval k
E_k	packet success indicator during update interval k
$\mathbf{x}_i$	traffic states of node i in CSMA networks
$\mathbf{M}$	covariance matrix of traffic states
T_{coef}	traffic change indicator
$1/t_i$	throughput demand of node i
$s(t), c(t)$	Markov states in the channel-state mode of CSMA networks
p_m	miss detection probability in a CSMA network
p_f	false positive probability in a CSMA network
$T(x)$	system throughput in a CSMA network with carrier sensing error
p_j	carrier sensing probability of node i in a random slot

1. Introduction

1.1 Recent Trends in Wireless Random Access Protocols

Random access protocols are a class of communication protocols in which each user transmits packets at random, as opposed to fixed access protocols such as time division multiple access (TDMA) whereby each packet is assigned a dedicated slot. Random access protocols have been widely used in various contemporary communication systems [1-4]. They offer a dynamic solution to assign bandwidth resources to a large set of users with randomly arriving traffic. When compared with fixed access protocols, the random access protocols are able to utilize the channel resources more efficiently and more flexibly when users in the network have low traffic loads [5].

Random access protocols can be broadly divided into two types: non-carrier-sensing protocols and carrier-sensing protocols. One of the representative non-carrier-sensing protocols is the ALOHA protocol. ALOHA has been playing a dominant role in cellular networks such as Global System for Mobile Communications (GSM) [6] and General Packet Radio Service (GPRS) [1]. In recent years, various derivatives of ALOHA protocol have been developed and considered promising for a wide spectrum of applications including wireless sensor networks [7], next generation Internet of Things (IoT) [3, 8], cognitive radio [9, 10] and smart grid [11], etc. In the context of carrier-sensing protocols, Carrier Sensing Multiple Access (CSMA) [12] and its variants have gained a renewed interest due to the emergence of wireless local area network (WLAN) such as IEEE 802.11 DCF (WiFi) [13] and wireless personal area network (WPAN) such as IEEE 802.15.4 (ZigBee) [14].

Due to the rapid adoptions of low-cost wireless devices such as wireless sensor/actuator nodes (e.g., TelosB [15] and MicaZ [16]) and mobile phones, several new trends in random access wireless protocols have emerged and the performance metrics of the network have diversified. As a result, some assumptions need to be carefully re-examined.

Firstly, WPAN and WLAN applications often consist of different types of devices. As a result, the packets generated by these devices may be of heterogeneous nature. Furthermore, WPAN and WLAN often involve both sensing and control tasks, which typically have lower traffic as compared with normal wireless data networks, but require each node to sustain certain throughput demand to guarantee system performance. For example, in a satellite attitude determination and control system, various sensor nodes need to successfully transmit a number of packets containing sensor measurements to the controller within a certain time interval in order for the control signal to be properly computed and executed. This poses challenges on the modeling of random access networks as previous studies would normally assume a homogeneous and saturated wireless network.

With the evolution of communication systems into distributed systems in recent years, it becomes more and more important to utilize locally available information. As there is a lack of central planning and coordination in distributed networks, local information is essential in estimating network environment, interference and optimizing the system performance. While there have been studies on the use of various types of local information, their potential has not been fully exploited. For example, in a Rayleigh-fading ALOHA network, the effective use of channel state information remains an

open issue; in a CSMA network, how to use local information to estimate heterogeneous traffic has not been fully investigated.

Most wireless nodes, being micro-electronic devices, can only be equipped with a limited power source [17]. Even for sophisticated mobile devices with wireless transmission capacity such as mobile phones and tablets, the energy consumption is also known to be a critical issue. As such, trade-offs must be made between high throughput and low energy consumption.

Lastly, for carrier-sensing protocols, low-cost wireless devices frequently employ a threshold-based energy detection method to perform carrier sensing. While its simplicity greatly reduces the hardware cost, it inevitably results in imperfect carrier sensing, i.e., idle channel may be detected as busy and *vice versa*. However, the assumption of perfect carrier sensing still plays an important role in most models of carrier sensing protocols [18]. As such, the actual system performance may deviate from what is predicted by the models.

In this thesis, new modeling techniques for random access protocols are investigated. New algorithms will be proposed to accommodate for the aforementioned trends, and to optimize the system performance under the new settings.

1.2 Motivations and Objectives

1.2.1 Distributed Throughput Optimization in Slotted ALOHA Networks

The first objective of this thesis is to explore the use of local information for transmission control and throughput improvement in a non-carrier-sensing random

access network. The most widely used non-carrier-sensing random access network, i.e., the slotted ALOHA, is examined in this work.

In recent decades, research works on ALOHA have been focused on the incorporation of channel state information (CSI) into the generic ALOHA protocol. Various works [19-22] have been proposed to study the throughput performance with the use of CSI. However, it is not systematically clear how the use of CSI will affect the throughput of an ALOHA network. It has been discussed in [21] that the use of CSI may lead to *Braess Paradox* [21, 23] and counterintuitively, the throughput is even lower than the case without the use of CSI. This naturally leads to the question on when to use and how to use the CSI?

In this thesis, we aim to thoroughly investigate the efficient use of CSI. Specifically, the target is to find out the condition of occurrence of *Braess Paradox* and reveal its relationship with the capture ratio and the SNR. In addition, this work also aims at proposing a distributed algorithm that is able to achieve the optimal throughput under various operating scenarios.

1.2.2 Heterogeneous Traffic Estimation in CSMA Networks

The IEEE 802.15.4 has become the *de facto* standard for wireless sensor networks [14] in a broad spectrum of applications such as home automation [24] and vehicle/satellite communications [25]. Slotted CSMA protocols have been implemented in the contention access portion of the IEEE 802.15.4 medium access control (MAC) layer. The flexibility offered by CSMA enables the implementation of distributed networks with heterogeneous devices [26]. While the ability to embrace heterogeneous devices extends the realm of sensor network applications, it also complicates the design process. In order to achieve good system-wide performance (e.g., energy efficiency, high

throughput) in a decentralized network, distributed algorithms must be developed on each participating node to estimate other nodes' traffic rates. In a homogeneous network where nodes can be characterized by the same properties (e.g., packet length and packet arrival rate), estimating the traffic is equivalent to estimating the number of nodes in the network, which has been extensively studied in previous works [27, 28]. However, in a heterogeneous network, nodes may vary in packet arrival rate and packet length, *etc.* How to characterize the traffic in such a network remains unknown.

Therefore, for the research in CSMA networks, the first objective is to fill the void of heterogeneous traffic estimation by proposing two new distributed algorithms. We aim at revealing the relationship between locally available information (e.g., busy channel probability and packet success rate) and the traffic rates, so as to provide a distributed modeling framework for throughput maximization.

1.2.3 Throughput Optimization in Heterogeneous CSMA Networks

Estimating heterogeneous traffic is the first step towards distributed throughput optimization. In a heterogeneous network, it is common that each node is assigned with a throughput demand. The throughput demands among the nodes in the network may be different. For example, in a wireless network control system, each sensor is required to report to the corresponding controller/actuator node on the status of the control system. The transmission period of each node is dependent on the dynamics of the corresponding control system for a conventional periodic computer control system [29] or, on the sensor measurements for an event-triggered/self-triggered control system [30, 31]. Existing works [32-34] tend to assume the homogeneity of the network and does not provide a feasible framework to address the different throughput demands. Without such a framework to guide the packet transmission, each node might not be

able to meet the throughput demand or transmit more data than necessary and thus result in energy inefficiency and introduce more network traffic.

Therefore, the next objective of this work is to investigate the heterogeneous traffic interactions in a CSMA network and propose an adjustment algorithm that can guide the transmission probability to a desired level.

1.2.4 Throughput Maximization in CSMA Networks under Imperfect Sensing

In addition to throughput adjustment in an unsaturated network, our next objective is to examine the upper bound of throughput in a non-persistent CSMA network under more realistic settings (i.e., imperfect sensing). One issue associated with low-cost wireless devices is the sensing errors introduced by threshold-based energy detector. Although various carrier sensing methods are available, threshold-based energy detector is the prevailing one in most sensor nodes (e.g., TelosB and MicaZ) due to its simplicity. The detector declares the channel to be busy when the energy in the designated channel is greater than the pre-defined threshold and *vice versa*. However, as the wireless channel is noisy by nature, using threshold alone inevitably results in two types of sensing errors. The first is called *miss detection*, which happens when the channel is busy but the result given by the detector is idle. The other one, named *false positive*, happens when the detector mistake an idle channel for a busy one.

These two types of errors could have a great impact on the performance of a CSMA network. However, most existing CSMA modeling approaches and distributed algorithms assume the ideal channel sensing and the effect of imperfect carries sensing has not been fully investigated.

Therefore, this work aims at investigating the effect of carrier sensing errors on the system throughput and revealing the throughput degradation due to sensing errors. We also aim at designing a distributed algorithm that is able to achieve throughput optimality under imperfect carrier sensing condition.

1.3 Main Contributions

The following lists the main contributions of this thesis:

- **Proposal and design of a distributed exponential CSI-based transmission algorithm for throughput maximization in a slotted ALOHA network**

A novel technique to better exploit the channel state information called adaptive CSI is proposed. An extensive comparative study has been conducted to benchmark the proposed method with conventional threshold-based CSI method and methods without the use of CSI. The main contributions of this work are as follows:

- 1) The proposed adaptive CSI can achieve up to 9.9% more throughput than the threshold CSI and no-CSI methods for a wide variety of systems. Moreover, it can result in up to 12.3% power reduction than the other two methods.
- 2) Two simple yet effective guidelines are generalized on how to choose the aforementioned three CSI-related methods to achieve maximum throughput or power efficiency for different system parameters and thus to avoid the occurrence of *Braess Paradox*.
- 3) A distributed algorithm for the adaptive CSI is proposed. It is shown that the algorithm can guarantee convergence and robustness against changes on the number of active nodes in the network.

- **Proposal and development of two distributed algorithms to estimate heterogeneous traffic in CSMA networks**

Two distributed algorithms are proposed to estimate the on-going traffic intensity of a heterogeneous network under two different scenarios. In the first case where the transmission rates of the nodes are different but the packet lengths are the same, the traffic can be estimated by making use of the busy channel probability. In the second case where the transmission rates and packet lengths are both different, a distributed model is proposed to relate the locally available information, namely the busy channel probability and packet success rate, to the transmission rates and the packet lengths of the nodes. The proposed algorithm has three main advantages:

- 1) Compared with conventional approaches that can only estimate homogeneous traffic in CSMA networks, the use of distributed models in the proposed approach enables the estimation of heterogeneous traffic.
- 2) The proposed algorithms only make use of local information and do not require any central coordination. It is thus suitable for distributed network applications.
- 3) The proposed algorithms are robust against traffic changes in the network.

- **Proposal and implementation of an algorithm for distributed transmission rate adjustment in heterogeneous CSMA networks**

With the use of the traffic estimation algorithms, a distributed algorithm is proposed to predict the packet success rate and automatically adjust the transmission rate to meet a pre-determined throughput demand. The proposed algorithm has two advantages:

- 1) The algorithm allows nodes to set different throughput demands as long as the overall throughput demand is below the network capacity. This feature offers more flexibility and is extremely useful for network control system applications where different control subsystems co-exist in the network.
 - 2) Compared with centralized Markov chain models, extensive experimental results show that the proposed algorithm is able to tackle changes in the network throughput profile and achieve higher accuracy.
- **Derivation of the throughput capacity of a non-persistent CSMA under imperfect carrier sensing; development of a distributed backoff algorithm for throughput optimality**

The maximum throughput of non-persistent CSMA under imperfect carrier sensing is derived. A novel probabilistic backoff protocol is proposed. This proposed protocol possesses two main advantages:

- 1) Compared with the generic IEEE 802.15.4 CSMA protocol, it can achieve the maximal throughput under both perfect carrier sensing and imperfect carrier sensing, regardless of the number of nodes in the network.
- 2) The proposed protocol is fully distributed and does not assume prior knowledge on the number of nodes in the networks.

1.4 Outline of Thesis

The rest of the thesis is structured as follows.

Chapter 2 provides a literature review of the related research in modeling, estimation and optimization of random access networks. The challenges and limitations of the existing works are also identified.

Chapter 3 proposes an adaptive algorithm to better exploit the channel state information (CSI). Compared with existing transmission strategies, the proposed algorithm is able to achieve higher throughput. Chapter 4 focuses on the modeling and estimation of heterogeneous traffic in an IEEE 802.15.4 network. Two distributed algorithms are proposed to characterize the on-going traffic in a CSMA network. Chapter 5 presents an adjustment algorithm to tune the transmission rate to meet the throughput demand in a heterogeneous CSMA network. It enables distributed bandwidth allocation with respect to a pre-defined throughput demand. Chapter 6 studies the effect of imperfect carrier sensing on the system throughput. The maximum throughput of a non-persistent CSMA network with sensing errors is derived. A new distributed backoff protocol is proposed to achieve the throughput-optimality.

Chapter 7 summarizes the research work and describes the directions of future work in estimation, parameter optimization in random access networks.

2. Literature Review

2.1 Introduction

The throughput performance of a random access network has been widely studied. In an ALOHA network, the throughput optimization is achieved by exploiting the state information and optimizing the transmission probability. In a CSMA network, the throughput is optimized by properly modeling the user interactions and exploiting the local information. This chapter briefly reviews the use of local information in both ALOHA and CSMA networks as well as the modeling techniques for CSMA network.

2.2 Transmission Rate Control in ALOHA Networks

The performance of an ALOHA network and its variants have been extensively studied [35-37]. These earlier works modeled the networks from a system perspective, focusing on system-level performance, e.g., system throughput. With the evolution of telecommunication systems into distributed systems in recent years [38], the focus has been shifted from the system perspective to the user perspective. As the network might be of heterogeneous nature, a system-level approach might be insufficient to differentiate each node's goal and action. Moreover, many users in the wireless networks are power-constrained and they may prefer power conservation over throughput maximization. As such, new techniques and performance metrics should be developed to better design the network [22, 39].

MacKenzie et al. [40] conducted the analysis of a slotted ALOHA from the perspective of a selfish user. It is shown that a game-theoretic approach [41] was able to provide insights into the equilibrium operating point [42, 43] and the network performance such as throughput from a decentralized perspective. Later works explored more realistic

settings by incorporating the CSI into the ALOHA model to enable each node to make channel-aware decisions [21, 22, 38, 44, 45].

From the perspective of a distributed network, the key to achieving satisfactory throughput performance in an ALOHA network is for each user to control its own transmission probability. This cannot be accomplished without knowing the network environment and the on-going traffic in the network. As nodes do not perform channel sensing in an ALOHA network, the channel state information issued from a base station is typically the only information available to estimate the network conditions, e.g., instantaneous channel fading and scattering. As such, it is crucial to determine a proper transmission strategy based on the channel state information.

Menache et al. [22] analyzed the Nash equilibria of a slotted ALOHA network in a fading collision channel. A strategy to use the CSI was proposed, which imposed a threshold on the CSI reading. When the instantaneous CSI is above some threshold, the node transmits a packet in the current slot. The Nash equilibria under this transmission strategy were investigated. One important discovery was that for a throughput demand profile that is lower than the network capacity, there always existed two stable working points where none of the nodes have the incentive to deviate. This work was subsequently generalized to power capture model [46] and SINR capture model [21] to better characterize the time-varying fading channels and the multi-packet reception capacity [47].

Intuitively, the use of CSI should lead to power-efficient outcomes as a node can choose not to send a packet under bad channel conditions to avoid wasting energy. In [22, 38, 48], CSI is exploited to enhance the throughput performance in a collision channel. However, it was shown in [21, 49] that for a channel model with capture

effect, a threshold-based CSI method may experience *Braess Paradox* [23], i.e., adding extra information to the network reduces the overall performance. Consequently, the achievable throughput may be even worse than that without CSI.

This paradox does not occur all the time. In ideal cases when the signal-to-noise ratio (SNR) approaches infinity, it will always occur and it is suggested in [21] not to use CSI in such cases. When the SNR is a finite number, however, the occurrence of *Braess Paradox* is quite intricate. It depends on the total number of nodes in the network, the capture ratio of the receiver and the average transmission probability of each node. In [21], it is shown that there is no simple rule to determine the occurrence of *Braess Paradox*. Thus it is difficult to decide whether to use CSI.

Moreover, most of the works were focused on the existence of the equilibrium points. The questions of if and how the system arrived at the equilibrium point were less addressed. Menache et al. [22] proposed a distributed mechanism for each node to converge to the equilibrium point. However, this approach has several drawbacks. First, the mechanism requires infinite times of update. It is thus energy consuming and computationally expensive. Second, it assumes that the throughput requirement is fixed while in reality, the requirement may change over time, e.g., nodes join/leave the network.

2.3 Modeling of CSMA Networks

Different from the simple ALOHA network, a CSMA network cannot be characterized by a single parameter (i.e., transmission probability). A CSMA protocol involves random backoff process and carrier sensing, which both strongly affect the network performance.

A mathematical model is instrumental in characterizing a CSMA network. A good model enables network designers to gain insights into a CSMA network and evaluate the network performance such as the packet success rate, the system throughput and the average packet delay beforehand. However, to derive such a model is challenging as nodes take actions randomly and consequently the network behavior tends to be difficult to predict. Moreover, there are a number of details associated with a practical CSMA protocol such as the setting of binary exponents, acknowledgement mechanism and the backoff algorithm. They all need to be taken into account when the modeling is performed.

Bianchi [50] proposed a bi-dimensional Markov chain to compute the saturated throughput of IEEE 802.11 CSMA network. The Markov chain, using the value of the backoff counter and the backoff stage, characterized the cyclic behavior of each saturated user. The interactions among different nodes are modeled through the collision probability. This model exhibits high accuracy in predicting the saturated throughput. However, it did not provide a framework to deal with unsaturated users. In addition, the simple model neglected the fact that the contention window may vary for different stages of retransmissions. It thus might not be accurate when the traffic load in the network heavy.

Ling et al. [51] presented a three-level renewal process [52] to model the slotted non-persistent CSMA as specified in the IEEE 802.15.4 standard. The model consisted of 3 renewal processes representing the process between two adjacent backoffs, the process between two adjacent packet transmissions and the process between two adjacent successful transmissions respectively. Saturated throughput was derived with negligible errors for both single carrier sensing and double carrier sensing cases. However, the

model did not consider the retransmission scheme either. Note that this work as well as the research done by Lee et al. [53] revealed a severe throughput degradation when the number of nodes is very large (e.g., larger than 40), implying that the generic IEEE 802.15.4 CSMA might not be suitable for large networks.

Park et al. [33, 54] provided a complete characterization of the IEEE 802.15.4 CSMA, considering acknowledgement packet and retransmission. Instead of using the approximation as in [50], a three-dimensional Markov chain was proposed, in which an additional state is used to account for the retransmission stage. A simple traffic model is employed to characterize both unsaturated and saturated traffic. The three-dimensional model achieved very high accuracy even when the traffic load was high mainly because of the addition of the new state. Moreover, an approximate analysis was performed in [54] which enabled nodes to estimate the performance metrics in a distributed manner. Each node is able to obtain an estimate of the packet success rate, the average delay and the energy consumption by keeping a record of its busy channel probability and the transmission probability. This approach was further used in [33, 55] to tune the MAC layer parameters achieve optimal system performance.

In [56], Faridi et al. conducted a comprehensive study scrutinizing the assumptions that the busy channel probability is constant for all backoff stages, which is commonly used [50, 53, 54]. It was discovered that in fact the busy channel probabilities for different backoff stages could be significantly different and the difference could have a noticeable impact on the performance metrics. Taking the difference into account, Faridi et al. proposed a semi-analytical approach to evaluate the network more accurately. However, the difference of busy channel probabilities at different stages is significant only when the network is not “randomly shuffled”, i.e., when there are only

a few nodes or when the data arrival rate is very low. When the network expands or when the traffic load is high, the difference becomes negligible.

All the above works focused on the microscopic aspect of the network, meaning that the modeling is performed on a single-node basis. It thus implies that all nodes have the same behavior. Indeed, homogeneity is commonly assumed in many studies on the performance metrics of CSMA networks [13, 57-59]. However, this assumption does not apply to most real-world CSMA network applications. For example, in a wireless sensor and actuator network [60], different control loops have different system dynamics and thus different sampling intervals. From a network perspective, the traffic generated by the nodes are heterogeneous and the above models cannot be used to evaluate the system performance.

Malone [61] extended Bianchi's model [50] to a unsaturated heterogeneous IEEE 802.11 CSMA network. In [62], Di Marco et al. applied the modeling approach in [54] to an unslotted IEEE802.15.4 CSMA network with heterogeneous unsaturated traffic. Kosek-Szott et al. [63] considered both the saturated and unsaturated traffic sources in a heterogeneous IEEE 802.11 network. The packet success rate and packet delay can be derived from these models. Although the models achieve high accuracy, they are very complex and require a full knowledge of network traffic. Solving the models also requires sophisticated numerical methods. They are thus not applicable when an in-network solution is expected.

Ashrafuzzaman et al. [32] proposed a dual-model approach to evaluate the system performance of CSMA networks. Instead of using a multiple state Markov chain model, the network dynamic is partitioned into two simple one-dimensional Markov chains, namely the node-state model and the channel-state model. While the node-state model

focuses on the backoff process, the channel-state characterizes the macroscopic aspect of the network. It makes use of the fact that each node needs to sense two consecutive idle slots before transmitting a packet and model the channel on an adjacent slot-pair basis. Although the model is based on the assumption of homogeneity, the channel-state model enables the throughput to be expressed as a function of network aggregate traffic rather than the number of nodes. It thus opens up new possibilities to extend the modeling approach to heterogeneous networks in a simple way. Moreover, despite the simplicity, the dual-model approach is able to achieve comparable accuracy in characterizing the throughput to that of a multiple-dimensional Markov chain model [33, 54, 57].

2.4 Exploitation of Local Information and Traffic estimation in CSMA networks

Local Information

In the context of a CSMA network, local information refers to information that each node is able to obtain simply by recording its own carrier sensing or transmission activities. Normally, local information is a by-product of the packet transmissions and does not cost extra energy. Local information is important in wireless sensor networks when estimating the network condition (e.g., traffic intensity) as coordinating message from a central node (e.g., beacon in IEEE 802.15.4 beacon-enabled mode) is usually unavailable. Moreover, when the network is organized in a distributed manner, the network condition may change over time (e.g., addition of new nodes) and it is desirable to make use of local information to capture the changes and adapt the actions of the nodes to the changes accordingly.

For a wireless node in a CSMA network, the obtainable information includes the following.

- i) Carrier sensing results: They can be obtained when nodes perform the clear channel assessment [64]. How frequently a node senses a busy channel reveals the traffic intensity of the network.
- ii) Packet success rate (or packet collision rate): It is available if the acknowledgement mode is activated. The packet success rate is an indication of the level of collisions in the network.
- iii) Channel sensing probability [33]: It is the probability that each node attempts a clear channel assessment in random slot. Channel sensing probability naturally reflects the corresponding node's level of channel occupation. Furthermore, when the network is homogeneous, it is also a reflection of the level of channel occupation of all other nodes.

Using any of the above or a combination of them can be effective in estimating the network condition qualitatively. Moreover, with the use of network models, the local information can be quantitatively exploited and translated to performance metrics and network indicators that are usually unmeasurable.

It is important to note that when the network condition is steady (e.g., constant traffic), there exists a nominal "true" value for each type of probability. However, this theoretical value is usually unobtainable. Instead, what each node obtains locally is a noisy measurement that is affected by several factors. Bianchi [50] gave a statistical characterization of the conditional collision probability. It is analyzed that the probability follows a binomial distribution and the parameter of the distribution is mainly determined by the number of samples collected during an update interval.

Intuitively, when the update interval is shorter, fewer samples are collected and consequently the measurement has more variations and noisier. Note that this analysis also applies to other types of probabilities obtained from local information.

Due to the noisiness of the measurements, they need to be properly filtered before being used for decision making. A simple smoothing filter is commonly used in network estimation [47, 55, 65] to trade off current and past measurements. It is shown that such a simple construct is able to avoid harmful fluctuation [47]. However, the selection of the smoothing factor is highly heuristic and there yet exists a systematic way to find the optimal smoothing factor. Smoother measurements can usually be expected when more weight is assigned to past measurements, it also results in high latency when adapting to traffic changes. Extended Kalman filter and particle filter were employed in [27] and [28] respectively to achieve more accurate estimation of conditional collision probability. These two methods are both able to differentiate between random fluctuations and traffic changes. However, latency is still expected when tracking the traffic changes.

Another approach to obtain more accurate measurements is to increase the duration of each update interval and thus to increase the number of samples collected during each interval. It is derived in [27] that the variance of the probability under investigation is inversely proportional to the number of samples. The work in [47] investigated the effect of update interval duration on the estimation of the number of active nodes in the network through simulations. Although it is clear that a longer update interval results in better measurements, it also significantly increases the reaction time adapting to traffic changes. Existing works tend to find the optimal update interval through extensive

simulations [66]. How to analytically optimize the update interval and the filter parameters (e.g., smoothing factor) remains an open issue.

Estimation Based On Local Information

Performance evaluation of networks has conventionally been carried out by extensive offline experimental measurements [67, 68]. By observing the parameter setting and corresponding results, one can gain firsthand information on how to optimize the network performance at the design phase. However, the performance in most cases can only be evaluated on a case-by-case basis and thus the results obtained cannot be applied for applications with different setups. As such, it is desirable to have a systematic approach to estimate and evaluate the performance metrics in an online manner.

Rivero-Angeles et al. [66] introduced a simple algorithm to estimate the on-going traffic loads for two variants of CSMA, namely NP-CSMA and 1P-CSMA. It first counted the number of idle slots and then calculated the traffic loads using the relation between probability of idle slots and the traffic loads derived in the paper. Park et al. [33] used the model in [54] to estimate the packet success rate, the average delay as well as the energy consumption per packet.

Bianchi et al. [27] explored the use of local information to estimate the number of active nodes in a homogeneous IEEE 802.11 network. Estimating the number of active nodes is important for system throughput performance as the optimal backoff window size needs to be selected based on it. This work attempted to obtain the conditional collision probability by counting the number of failed transmissions during a time interval. Then the conditional collision probability is related to the number of active nodes using the bi-dimensional Markov chain model in [50]. An extended Kalman-

filter based approach was used to achieve more accurate estimation. Furthermore, a change detection filter was also implemented to detect changes in the number of active nodes. It is thus suitable for a distributed network with device association/dissociation. This work was followed by Bayesian approach proposed in [28]. With the use of a Monte Carlo estimator [69], this approach achieves better estimation accuracy compared with that of an extended Kalman filter. Lim et al. improved the estimation accuracy by employing H-infinity filter [70]. This approach does not require the use a state variation detector and as a result, the estimator does not suffer from the latency effect that are encountered in [27, 28]. Bae et al. [47] extended the estimation of the number of active nodes to networks with multi-packet reception capacity.

The above works, however, considered only homogeneous networks with saturated nodes. It is only under such scenarios that the network conditions such as the traffic loads can be characterized by one single parameter (the number of active nodes). Models that can be used for local estimation mostly relied on ideal assumptions [47, 50, 54] and more realistic models that consider heterogeneity, unsaturation and different types of traffic patterns [63, 71] are difficult to be approximated and used in a distributed manner.

2.5 Distributed Optimization using Local Information

Performance improvements can be made by using local information. Typically, performance is optimized by choosing the CSMA parameters such as binary exponents, backoff limit and retry limit. A representative optimization problem can be formulated as follows [65, 72]:

$$\min_{\mathbf{Par}} E(\mathbf{Par}) \quad (2-1)$$

$$\text{s.t. } R(\mathbf{Par}) \geq R_{\min}$$

$$D(\mathbf{Par}) \leq D_{\max}$$

where $\mathbf{Par}$ is the set of CSMA parameter setting, $E(\mathbf{Par})$ is the average energy consumption for each packet, $R(\mathbf{Par})$ is the reliability (i.e., packet success rate) and $R_{\min}$ is imposed requirement on the reliability, and $D(\mathbf{Par})$ is the average delay per packet and $D_{\max}$ the maximum permissible delay.

The existing optimization methods can be broadly divided into two categories: model-based strategies and measurement-based strategies.

Model-based strategies rely on analytical models such as the ones in Section 2.3 [72]. They use the model to relate the CSMA/CA parameter setting to the network performance. It can be achieved by solving the exact analytical model, which is typically a multi-dimensional Markov chain model. This method requires a large amount of computation resources and is generally not applicable for resource-constrained wireless modules [33]. Alternatively, an approximate version of the analytical model can be used and the performance metrics can be computed using the local information in a distributed manner. However, the computation is still intensive.

For both the accurate and simplified models, the performance heavily depends on the accuracy of the underlying models [72]. Moreover, as discussed in Section 2.3, most models require certain parameters' values such as the number of nodes in the network, which is normally unavailable in a distributed network.

Measurement-based strategies do not require an analytical model but tune the CSMA/CA parameters simply based on the network operating conditions (e.g., traffic intensity). Francesco et al. [58] proposed the *ADaptive Access Parameters Tuning*

(ADAPT) algorithm that dynamically tunes the CSMA/CA parameters to adapt to the network operating conditions. Specifically, ADAPT algorithm increases or decreases the CSMA/CA parameters based on local measurements of packet success rate. The ADAPT does not require prior information on network and can be practically used for any network scenarios [58, 72]. However, the ADAPT has the issue of oscillating between adjacent parameters and never stabilizing the system under a given constraint. Brienza et al. [72] presented a learning-based tuning algorithm called LEAP. LEAP remedied the issue of instability encountered in [58] using data from past history. A learning table was introduced [72, 73] to relate the network operating conditions to the optimal CSMA parameter settings. If the same operating conditions repeat over time, the optimal parameters can then be found from table without taking time to iteratively converge to the optimum.

The necessity of using a table is that the relationship between the network operating conditions and the CSMA parameters cannot be explicitly derived. It can only be constructed one by one using historical data [72, 73] or simulation data [33]. However, the main problem is that although the computation time can be reduced to minimum, more memory space is required to store the learning table [72, 73] or an off-line look-up table [33]. As the CSMA parameters set is usually multi-dimensional, the search space could be significantly large. For example, the algorithm in [33] was implemented in the hardware module named TelosB [74] using the C language and the look-up table in the form of a C-array takes up more than 500kB space.

The above works focused on performance improvements at a system level. The optimization problems required no modification of the IEEE 802.15.4 standard. From a practical perspective, adhering to the standard is favorable as the algorithms can be

readily implemented on top of existing protocol stacks at a minimal cost. However, the IEEE 802.15.4 CSMA protocol suffers from some well-known drawbacks such as low throughput performance [75-78], unnecessary channel sensing [79] and hidden nodes [80, 81], *etc.* Despite the best efforts on parameter tuning, the performance improvements are relatively limited.

There are other research works investigating the performance improvements through slight modifications of the standard. Most of them targeted at altering the binary exponent backoff used in IEEE 802.15.4 CSMA. Ha et al. [79] explored the use of clear channel assessment (CCA) results to determine the expected length of the ongoing packet and proposed a tuning algorithm to determine an energy-efficient backoff period. Abdeddaim et al. [75] applied the modeling method of IEEE 802.11 MAC [50, 61] to IEEE 802.15.4 MAC and proposed an adaptation contention window to optimize the throughput performance. However, it requires the central receiver to perform the estimation and optimization and it is thus not applicable in distributed networks. Moreover, the use of modeling framework of IEEE 802.11 for IEEE 802.15.4 network is also questionable since they employed different carrier sensing mechanisms (continuous carrier sensing *versus* sporadic carrier sensing) and the packet collisions cannot be characterized by the same model. Lee et al. [82] showed the throughput performance improvement and collision reduction by introducing a delayed backoff algorithm. Kim [64] examined the use of double carrier sensing in the clear channel assessment and showed that it was unnecessary under many scenarios. A short clear channel assessment was then proposed to shorten the carrier sensing and increase the transmission attempts. Lee et al. [83] identified the same inefficiency issue of double carrier sensing and proposed a 3-slot clear channel assessment method to differentiate between data packet and acknowledgment packet. The knowledge on the type of

packets results in better transmission strategy and hence higher throughput and lower energy consumption. Yassien et al. [84] explored the use of Fibonacci sequence for backoff process. It was shown that with a proper tuning, this method could possibly achieve higher throughput.

Despite the performance improvement, these works are of a heuristic nature and there is a lack of systematic approach when designing the algorithm. Moreover, with the modification of the IEEE 802.15.4 CSMA/CA protocol, new parameters were introduced and they also needed to be optimized. In [84], subtle tuning of the length of Fibonacci sequence was required to achieve good throughput. However, it is very difficult to determine the optimum length.

2.6 Summary

This chapter reviews the background and existing work on the use of local information, modeling methods, distributed estimation and distributed optimization in random access networks. A summary on the related works is given as follows:

- For the slotted ALOHA network, there have been extensive works studying its throughput performance under various settings. Specifically, the use of channel state information for optimal distributed transmission control has been explored. However, it is unclear how to effectively use the channel state information under different noise and interference levels as well as different receiver specifications.
- For the modeling of CSMA networks, a lot of works have been proposed to model the user interaction and the random backoff process. These studies provide good methods to characterize the network performance. However, most of the existing models are of high computational complexity and can

hardly be solved in a distributed manner. Moreover, the assumptions of homogeneous and saturated traffic are prevalent in most works.

- The high complexity of the existing models also poses challenges on estimating on-going traffic in a CSMA network. In a network where traffic may change over time, it is almost impossible to repetitively solve the multi-dimensional Markov chain models. Although simplified models have been developed to characterize the network performance metrics in a distributed manner, they typically have not considered the heterogeneity of the traffic.
- For the throughput performance of an IEEE 802.15.4 CSMA network, it has been found out that the protocol tends to result in sub-optimal throughput performance. There have been a lot of works proposing enhanced methods to achieve higher throughput. However, these works are of heuristic nature and little attention has been paid to the theoretical upper bound of the throughput and how to achieve throughput-optimality. Moreover, most of the existing works neglect the possible carrier sensing error and its effect on the throughput performance.

In the following chapters, new algorithms are proposed to address the abovementioned issues. Chapter 3 examines the use of channel state information and proposes a new transmission control strategy that can exploit the channel state information more effectively for higher throughput. In Chapter 4, the distributed modeling and heterogeneous traffic estimation are addressed. In Chapter 5, a distributed throughput adjustment algorithm is proposed to enable each node to tune its throughput to meet the desired throughput demand. In Chapter 6, the upper bound of the throughput of a non-persistent CSMA under imperfect carrier sensing is explored. A novel backoff algorithm is also proposed to achieve throughput optimality.

3. Distributed Transmission Probability Control in Rayleigh-fading ALOHA Networks

3.1 Introduction

In Chapter 2, the state of the art of the ALOHA network was reviewed. The use of channel state information (CSI) for throughput optimization was discussed. As mentioned, the use of CSI was limited to a threshold-based strategy, which tends to result in the *Braess Paradox* and poor throughput performance.

In this chapter, the use of CSI is thoroughly examined and a new method to exploit the CSI named adaptive CSI is proposed. The objective of the adaptive CSI is to achieve better throughput performance in a slotted ALOHA network. The main advantages of the proposed method are as follows:

- The proposed adaptive CSI can achieve up to 9.9% more throughput than the threshold CSI and no-CSI methods for a wide variety of systems. Moreover, it can result in up to 12.3% power reduction than the other two methods.
- The occurrence of *Braess Paradox* [21] can be avoided. Two simple yet effective guidelines are generalized on selecting the aforementioned three CSI-related methods to achieve maximum throughput or power efficiency under different system scenarios.
- A distributed algorithm is proposed to tune the transmission probability to the optimal point. This algorithm can guarantee fast convergence and is robust against changes in the number of active nodes in the network.

3.2 Preliminaries

3.2.1 Throughput

In the following, a wireless network where there are n nodes transmitting packets at a pre-determined power level to a base station over a shared channel is considered. It is assumed that the time is slotted and the amount of information contained in a data packet is fixed and is the same for all the nodes. A data packet, with the possible acknowledgement packet, occupies one time slot. Each node contends for the channel access using the slotted probabilistic ALOHA protocol. In each time slot k , each node i transmits with a transmission probability $p_{i,k}$. Each node is assigned with an average throughput demand ρ_i . In this network, each node tries to minimize its overall power investment, which is equivalent to minimizing the transmission probability, while meeting the average throughput demand ρ_i . It is assumed that all the nodes have packets buffered for transmission at any time and the essential problem for each node is to choose a transmission strategy that fulfills its goal. Moreover, all the nodes are assumed to be well synchronized.

For the brevity of the analysis, the average throughput for node i is defined as the ratio of the number of packets that are successfully received by the base station to the total number of time slots. For example, if a node i transmits 100 packets to the base station during a 10000-slot period, of which 67 are successful, then the average throughput for node i is 0.0067.

3.2.2 Fading Channel and SINR Capture

Signal-to-interference-and-noise ratio (SINR) capture [21] is used to model the fading channel. In the SINR model, node i 's packet at time k will be successfully received by

the base station if $SINR_{i,k} > b$ [21], where b is the radio capture ratio and $SINR_{i,k}$ is the SINR of node i at time slot k . $SINR_{i,k}$ is given by

$$SINR_{i,k} = \frac{B_{i,k} |h_{i,k}|^2 P_T}{\sum_{j \neq i} B_{j,k} |h_{j,k}|^2 P_T + N} \quad (3-1)$$

where N is the average power of the additive noise at the base station and P_T is the transmission power of each node. $B_{i,k} = 1$ if node i transmits a packet at time slot k and $B_{i,k} = 0$ otherwise. $h_{i,k}$ is the channel gain between node i and the base station at time k . The physical intuition of the SINR model can be traced back to the capture effect of a radio receiver. Only when the signal from a particular node i is at least b times stronger than the interference then it can be amplified and successfully decoded [85].

In the sequel, it is assumed that the channel is an *i.i.d Rayleigh Fading* channel and $x_{i,k} = |h_{i,k}|^2$ are thus assumed to be an *i.i.d* uniformly exponential random variable, fixed within one slot and varying from one slot to another as in [21, 86]. It is further assumed that at the beginning of the time slot k , each node i is able to obtain its own instantaneous channel state information, which provides an indication of the quality of the channel. Furthermore, each node can obtain $h_{i,k}$ and thus $x_{i,k}$ from the CSI reading, as in [21].

3.2.3 Adaptive CSI-based Transmission Method

A novel method named adaptive CSI-based method is proposed. Instead of using a fixed threshold-based CSI strategy as in [21], the proposed method considers the fact that $x_{i,k}$ is exponentially distributed. A complementary function $c_i(1 - e^{-x_{i,k}})$ is constructed to dynamically determine the transmission probability $p_{i,k}$ with respect to

the instantaneous CSI, where $c_i \in (0, 1)$ is a tuning factor determining the amplitude of the transmission probability. The intuition of the adaptive CSI-based transmission is that the transmission probability is made to be proportional to “how good the channel is”. This method can be defined as follows:

Definition 3.1: an *adaptive CSI-based transmission strategy* for node i in time slot k is defined as a mapping from $x_{i,k}$ to $p_{i,k} \in [0, 1]$ and has the form of $p_{i,k} = c_i(1 - e^{-x_{i,k}})$. Moreover, the node i transmits a packet in slot k with a probability $p_{i,k}$. $\square$

It can be concluded that $p_{i,k}$ is a monotonically increasing function of the channel state $x_{i,k}$. It also immediately follows that the average transmission probability of node i is solely determined by c_i and is given by

$$p_i(c_i) = \int_0^\infty c_i(1 - e^{-x_{i,k}}) e^{-x_{i,k}} dx_{i,k} = \frac{c_i}{2} \quad (3-2)$$

3.2.4 Acknowledgement Information

It is assumed that an acknowledgement (ACK) packet issued from the base station is available upon each successful transmission. By recording all its ACK results for a certain period, each node can determine the average packet success rate p_{PSR} for that period. The p_{PSR} for the current period can be used to determine the game strategy. The game strategy is updated every I time slot and each node keeps a record of the ACK packets in the form of p_{PSR} between 2 consecutive update instants. The p_{PSR} will be erased to 0 upon each update and reflects only the traffic and channel conditions in the current update interval.

3.3 Equilibrium Analysis

3.3.1 Power Optimization Problem

According to the problem formulation, the local optimization problem for each node i using the adaptive CSI method can be modeled as

$$\begin{aligned} \min_{p_i} p_i(c_i) \\ \text{subject to } r_i(p_i, \mathbf{p}_{-i}) \geq \rho_i \end{aligned} \quad (3-3)$$

where $\mathbf{p} = (p_1, p_2, \dots, p_n)$ is the transmission probability vector, $r_i(p_i, \mathbf{p}_{-i})$ is the average throughput of node i when it transmits with probability p_i given that others transmit with probability $\mathbf{p}_{-i}$, where $\mathbf{p}_{-i}$ represents the transmission probability vector of all nodes except node i . ρ_i is the throughput demand for node i .

The system can be modeled as a constrained non-cooperative game. Each node acts as a selfish entity, taking actions. It chooses the tuning factor c_i and thus the transmission probability p_i [21, 39, 44] to minimize its own power investment subject to the throughput constraint.

3.3.2 Nash Equilibria

It is assumed that each p_i takes a value from $[0, 1]$. A utility function can be defined as $U_i(p_i, \mathbf{p}_{-i}) = 1 - p_i$. Higher transmission probability results in higher power investment and thus lower utility. With the utility function, the following definition on Nash equilibrium can be established.

Definition 3.2: an action profile $\mathbf{p}$ is a constrained *Nash Equilibrium* point if for all $i = 1, 2, \dots, n$, there exists

$$\begin{cases} r_i(p_i, \mathbf{p}_{-i}) \geq \rho_i \\ U_i(p_i, \mathbf{p}_{-i}) \geq U_i(\tilde{p}_i, \mathbf{p}_{-i}), \text{ all } (\tilde{p}_i) \in \{\tilde{p}_i: r_i(\tilde{p}_i, \mathbf{p}_{-i}) \geq \rho_i\} \end{cases} \quad (3-4)$$

where $\tilde{p}_i$ is the transmission probability of node i such that its throughput demand can be fulfilled. $\square$

Equivalently, $\mathbf{p}$ is a Nash equilibrium if

$$p_i \in \arg \min_{0 \leq \tilde{p}_i \leq 1} \{ \tilde{p}_i: r_i(\tilde{p}_i, \mathbf{p}_{-i}) \geq \rho_i \} \quad (3-5)$$

Since $r_i(p_i, \mathbf{p}_{-i})$ and $U_i(p_i, \mathbf{p}_{-i})$ are nondecreasing functions of p_i under the SINR model, it immediately follows as in [21] that $\mathbf{p}$ is a Nash equilibrium if and only if it is a solution to the set of equations

$$r_i(p_i, \mathbf{p}_{-i}) = \rho_i, i = 1, 2, \dots, n \quad (3-6)$$

3.3.3 Existence of Nash Equilibrium

When there are $s (s \leq n)$ nodes using the adaptive CSI strategy to transmit a packet to the base station at the same time slot, the probability that the packet received successfully from a particular node i is given as

$$\int_0^\infty \dots \int_0^\infty c_1 (1 - e^{-x_1}) \int_{b \sum_{j \neq i} x_j + b \frac{N}{P_T}}^\infty c_i (1 - e^{-x_i}) e^{-x_i} dx_i e^{-x_1} dx_1 \dots e^{-x_s} dx_s \quad (3-7)$$

Solving (3-7) yields

$$e^{-b \frac{N}{P_T}} \left(\prod_{\substack{j=1 \\ j \neq i}}^s \frac{c_j}{(1+b)(2+b)} - \frac{1}{2} \frac{c_j}{(1+2b)(2b+2)} \right) \quad (3-8)$$

Using (3-2) and denoting $x_1 = (1 + b)(2 + b)$ and $x_2 = (1 + 2b)(2b + 2)$ for brevity, the following theorem on the average throughput of node i using the proposed adaptive CSI method can be formulated.

Theorem 3.1: Under the SINR capture model with capture ratio b , and *i.i.d.* Rayleigh fading channels between all nodes and the base station, the average throughput of node i when the transmission probability vector is $\mathbf{p} = (p_1, p_2, \dots, p_n)$ and when each node uses the adaptive CSI transmission strategy is as follows

$$\begin{aligned}
 r_i(p_i, \mathbf{p}_{-i}) = & p_i \left(2e^{-b\frac{N}{P_T}} - e^{-2b\frac{N}{P_T}} \right) \prod_{j \in Q_{-i}} (1 - p_j) \\
 & + p_i e^{-b\frac{N}{P_T}} \left(2 \prod_{j \in Q_{-i}} \left(\frac{2p_j}{x_1} + 1 - p_j \right) \right. \\
 & \left. - \prod_{j \in Q_{-i}} \left(\frac{2p_j}{x_2} + 1 - p_j \right) \right)
 \end{aligned} \tag{3-9}$$

where Q_{-i} is the set of all the nodes in the network except node i . The Nash equilibrium is achieved when $r_i(p_i, \mathbf{p}_{-i}) = \rho_i$ for every node i in the network. $\square$

Proof: The theorem can be proved by Binomial theorem and is similar to *Lemma 1* in [21].

The throughput of node i can be computed as

$$r_i(p_i, \mathbf{p}_{-i}) = \prod_{j \in Q_{-i}} (1 - p_j) \int_{b\frac{N}{P_T}}^{\infty} c_i (1 - e^{-x_i}) e^{-x_i} dx_i$$

$$\begin{aligned}
& + p_i \sum_{j \in Q_{-i}} \left(p_j \left(\prod_{k \in Q_{-\{j,i\}}} (1 - p_k) \right) \right) e^{-b \frac{N}{P_T}} \left(\frac{c_j}{(1+b)(2+b)} \right. \\
& \left. - \frac{1}{2} \frac{c_j}{(1+2b)(2b+2)} \right) \\
& + p_i \sum_{\{j,k\} \in Q_{-i}} \left(p_j p_k \left(\prod_{l \in Q_{-\{j,i,k\}}} (1 - p_l) \right) \right) e^{-b \frac{N}{P_T}} \left(\prod_{m \in \{j,k\}} \frac{c_m}{(1+b)(2+b)} \right. \\
& \left. - \frac{1}{2} \frac{c_m}{(1+2b)(2b+2)} \right) + \dots \\
& + p_i \left(\prod_{j \in Q_{-i}} p_j \right) e^{-b \frac{N}{P_T}} \left(\prod_{m \in Q_{-i}} \frac{c_m}{(1+b)(2+b)} - \frac{1}{2} \frac{c_m}{(1+2b)(2b+2)} \right) \\
& = p_i \left(2e^{-b \frac{N}{P_T}} - e^{-2b \frac{N}{P_T}} \right) \prod_{j \in Q_{-i}} (1 - p_j) \\
& + p_i e^{-b \frac{N}{P_T}} \left(2 \prod_{j \in Q_{-i}} \left(\frac{2p_j}{x_1} + 1 - p_j \right) - \prod_{j \in Q_{-i}} \left(\frac{2p_j}{x_2} + 1 - p_j \right) \right)
\end{aligned}$$

From (3-9), the following 2 corollaries can be given.

Corollary 3.1: the average packet success rate of node i is given as

$$\begin{aligned}
p_{PSR_i} = & \left(2e^{-b \frac{N}{P_T}} - e^{-2b \frac{N}{P_T}} \right) \prod_{j \in Q_{-i}} (1 - p_j) + e^{-b \frac{N}{P_T}} \left(2 \prod_{j \in Q_{-i}} \left(\frac{2p_j}{x_1} + \right. \right. \\
& \left. \left. 1 - p_j \right) - \prod_{j \in Q_{-i}} \left(\frac{2p_j}{x_2} + 1 - p_j \right) \right)
\end{aligned} \tag{3-10}$$

Corollary 3.2: when all the nodes have the same throughput demand ρ , the average throughput of each node can be simplified as

$$r = p \left(2e^{-b \frac{N}{P_T}} - e^{-2b \frac{N}{P_T}} \right) (1 - p)^{n-1} + p e^{-b \frac{N}{P_T}} \left(2 \left(\frac{2p}{x_1} + 1 - p \right)^{n-1} - \right. \tag{3-11}$$

$$\left(\frac{2p}{x_2} + 1 - p\right)^{n-1}$$

To determine the existence of Nash equilibrium, the derivative of r is derived as

$$\begin{aligned} \frac{dr_{a-CSI}}{dp} = & (1 - np) \left(2e^{-b\frac{N}{P_T}} - e^{-2b\frac{N}{P_T}} \right) (1 - p)^{n-2} + e^{-b\frac{N}{P_T}} \left(2 \left(\frac{2p}{x_1} + \right. \right. \\ & 1 - p \left. \left. \right)^{n-2} \left(1 - \left(1 - \frac{2}{x_1} \right) np \right) - \left(\frac{2p}{x_2} + 1 - p \right)^{n-2} \left(1 - \left(1 - \right. \right. \\ & \left. \left. \frac{2}{x_2} \right) np \right) \right) \end{aligned} \quad (3-12)$$

It can be seen that $\frac{dr_{a-CSI}}{dp} > 0$ when $0 < p < 1/n$ and there exists a $p^* > 1/n$ such that when $1/n < p < p^*$, $\frac{dr_{a-CSI}}{dp} > 0$ and when $p > p^*$, $\frac{dr_{a-CSI}}{dp} < 0$. Thus, when the throughput demand is achievable (i.e., $r^{max} \geq \rho$), there exists one (i.e., when $r^{max} = \rho$) or two (i.e., when $r^{max} > \rho$) Nash equilibrium points.

When there are two equilibrium points, the one associated with smaller transmission probability is superior to the other in terms of minimizing power investment. This immediately follows from the fact that power investment is an increasing function of transmission probability.

Moreover, simulation results show that for heterogeneous networks, there exists at least one equilibrium point given that the throughput demand is feasible.

3.4 Maximal Throughput Analysis

In Section 3.3, the Nash equilibrium of (3-3) is analyzed. The relationship between throughput demand and transmission probability is derived for the adaptive CSI scheme. In this section, the maximum achievable throughput of the adaptive CSI

scheme is compared with the two other schemes in [21], namely threshold-based CSI method and no-CSI method.

For the no-CSI method, the throughput is given by [21] as follows:

$$r_{\text{no-CSI}} = e^{-b\frac{N}{P_T}p} \left(1 - \frac{bp}{1+b}\right)^{n-1} \quad (3-13)$$

It can be seen that the maximal throughput is obtained when $p = (b+1)/bn$ and the throughput when $p = (b+1)/bn$ is as follows:

$$r_{\text{no-CSI}}^{\max} = e^{-b\frac{N}{P_T}\frac{b+1}{bn}} \left(1 - \frac{1}{n}\right)^{n-1} \quad (3-14)$$

For the threshold-based CSI method, the throughput is given by [21]:

$$r_{t\text{-CSI}} = e^{-b\frac{N}{P_T}\left(\frac{p^{b+1}}{1+b} + (1-p)\right)^{n-1}} + (1-p)^{n-1} \min\left\{p - e^{-b\frac{N}{P_T}}, 0\right\} \quad (3-15)$$

When $p \leq e^{-bN/P_T}$,

$$\begin{aligned} \frac{dr_{t\text{-CSI}}}{dp} &= e^{-b\frac{N}{P_T}\left(\frac{p^{b+1}}{1+b} + (1-p)\right)^{n-2}} (n-1)(p^b - 1) + (1-p)^{n-1} \\ &\quad - (n-1)(1-p)^{n-2}(p - e^{-b\frac{N}{P_T}}) \end{aligned} \quad (3-16)$$

When $p > e^{-bN/P_T}$,

$$\frac{dr_{t\text{-CSI}}}{dp} = e^{-b\frac{N}{P_T}\left(\frac{p^{b+1}}{1+b} + (1-p)\right)^{n-2}} (n-1)(p^b - 1) \quad (3-17)$$

It is observed that there exists a unique solution $p = p^*$ for $\frac{dr_{t\text{-CSI}}}{dp} = 0$. When $p < p^*$,

$\frac{dr_{t\text{-CSI}}}{dp} > 0$ and when $p > p^*$, $\frac{dr_{t\text{-CSI}}}{dp} < 0$. When $p = p^*$, the maximum throughput is

achieved. However, p^* is difficult to obtain analytically due to the complexity of (3-16)

and (3-17). Notice that when b is large (e.g., $b = 3$), $p^b \approx 0$ as the transmission probability p is typically very small. Thus (3-16) can be approximated as

$$\begin{aligned} \frac{dr_{t\text{-CSI}}}{dp} \approx & \left(e^{-b\frac{N}{P_T}}(1-n) + (1-p) \right. \\ & \left. - (n-1) \left(p - e^{-b\frac{N}{P_T}} \right) \right) (1-p)^{n-2} \end{aligned} \quad (3-18)$$

and it can be seen that $p^* = 1/n$.

Moreover, assuming $p^b \approx 0$, (3-17) can be approximated as

$$\frac{dr_{t\text{-CSI}}}{dp} = -e^{-b\frac{N}{P_T}}(1-p)^{n-2}(n-1) \quad (3-19)$$

where $\frac{dr_{t\text{-CSI}}}{dp} < 0$ given that $0 < p < 1$.

Combining (3-18) and (3-19), it can be shown that $p^* = \min\{1/n, e^{-bN/P_T}\}$. In practical systems, it is almost certain that $1/n < e^{-bN/P_T}$. Thus, it is sufficient to discuss the case $p^* = 1/n$ only.

When $1/n < e^{-bN/P_T}$, the maximum throughput of the threshold-based CSI is given by

$$r_{t\text{-CSI}}^{\max} = e^{-b\frac{N}{P_T}} \left(\frac{n^{-(b+1)}}{1+b} + \left(1 - \frac{1}{n}\right) \right)^{n-1} + \left(1 - \frac{1}{n}\right)^{n-1} \left(\frac{1}{n} - e^{-b\frac{N}{P_T}} \right) \quad (3-20)$$

Similar to the threshold based CSI method, when b is large (e.g., $b = 3$), $1/x_1 \approx 1/x_2 \approx 0$, (3-12) can be approximated as

$$\begin{aligned} \frac{dr_{a\text{-CSI}}}{dp} &\approx (1 - np) \left(2e^{-b\frac{N}{P_T}} - e^{-2b\frac{N}{P_T}} \right) (1 - p)^{n-2} \\ &+ e^{-b\frac{N}{P_T}} (1 - np) (1 - p)^{n-2} \end{aligned} \quad (3-21)$$

The unique solution such that $\frac{dr_{a\text{-CSI}}}{dp} = 0$ is $p^* = 1/n$ and the maximum throughput is given by

$$\begin{aligned} r_{a\text{-CSI}}^{\max} &= \frac{1}{n} \left(2e^{-b\frac{N}{P_T}} - e^{-2b\frac{N}{P_T}} \right) \left(1 - \frac{1}{n} \right)^{n-1} \\ &+ \frac{1}{n} e^{-b\frac{N}{P_T}} \left(2 \left(1 - \left(1 - \frac{2}{x_1} \right) \frac{1}{n} \right)^{n-1} \right. \\ &\quad \left. - \left(1 - \left(1 - \frac{2}{x_2} \right) \frac{1}{n} \right)^{n-1} \right) \end{aligned} \quad (3-22)$$

Comparing (3-22) with (3-14) and (3-20), the following theorem on the maximum throughput can be established.

Theorem 3.2: given a capture ratio b and a network size n , when

$$m_l(b, n) < SNR < m_h(b, n) \quad (3-23)$$

the adaptive CSI method results in higher maximum throughput than the no-CSI method and the threshold-based CSI method, where $SNR = P_T/N$, $m_l(b, n) =$

$$\begin{aligned} &\frac{-b}{\ln\left(\frac{-(a_1 - a_2 - a_2/n - a_3/n) - \sqrt{(a_1 - a_2 - a_2/n - a_3/n)^2 - 4(a_2/n)^2}}{2n/a_2}\right)} \quad m_h(b, n) = \frac{-b}{\ln\left(\frac{a_3 - a_2/b}{a_2}\right)}, \quad a_1 = \left(\frac{n^{-(b+1)}}{1+b} + \right. \\ &\left. \left(1 - \frac{1}{n}\right)^{n-1}\right), \quad a_2 = \left(1 - \frac{1}{n}\right)^{n-1}, \quad \text{and} \quad a_3 = 2 \left(1 - \left(1 - \frac{2}{x_1}\right) \frac{1}{n}\right)^{n-1} - \left(1 - \left(1 - \frac{2}{x_2}\right) \frac{1}{n}\right)^{n-1}. \end{aligned}$$

Proof: the proof can be completed by enforcing $r_{a\text{-CSI}}^{\max} > r_{t\text{-CSI}}^{\max}$ and $r_{a\text{-CSI}}^{\max} > r_{\text{no-CSI}}^{\max}$ with proper algebraic manipulations.

It also follows that when $SNR \leq m_l(b, n)$, the threshold-based CSI method yields higher maximum throughput; when $SNR \geq m_h(b, n)$, it suffices to use the no-CSI method. The intuition is that when the channel is good enough, there is no need to confine the transmission to the “good” slots; when the channel is bad, the transmission should not be conducted at those bad slots at all; when the channel state is in between, there exists a wide gap where the CSI should be exploited in the proposed way.

Using (3-14), (3-20) and (3-22), the maximum throughput of each method under different capture ratios b and network sizes n can be obtained. Figure 3-1 compares the maximum throughput of the three methods. It is shown that there exists a red region in terms of SNR and capture ratio where the proposed adaptive CSI results in the highest throughput among the three methods. This improvement in throughput can be up to 9.9% as compared with the highest throughput that can be achieved by the no-CSI and threshold-based CSI methods.

Figure 3-1 Maximum Throughput with Different SNRs (dB) and Capture Ratios

3.5 Power Efficiency Analysis

Given the same transmission probability p (i.e., the same power investment) and using (3-11)--(3-13), the adaptive CSI method outperforms the no-CSI method when $r_{a-CSI} > r_{no-CSI}$. Solving the inequality for SNR yields

$$SNR < t_h(b, n, p) \quad (3-24)$$

$$\text{where } t_h(b, n, p) = \frac{-b}{\ln \left(\frac{2 \left(\frac{2p}{x_1} + 1 - p \right)^{n-1} - \left(\frac{2p}{x_2} + 1 - p \right)^{n-1} + (1-p)^{n-1} - \left(1 - \frac{bp}{1+b} \right)^{n-1}}{(1-p)^{n-1}} \right)}.$$

Similar comparisons can be made between (3-11) and (3-15). Solving the inequality $r_{a-CSI} > r_{t-CSI}$ for SNR yields

$$SNR < t_h(b, n, p) \quad (3-25)$$

$$\text{where } t_l(b, n, p) = \frac{-b}{\ln\left(\frac{-(a'_1 - a'_2 - a'_2 p - a'_3 p) - \sqrt{(a'_1 - a'_2 - a'_2 p - a'_3 p)^2 - 4(a'_2 p)^2}}{2/(a'_2 p)}\right)},$$

$$a'_1 = \left(\frac{p^{b+1}}{1+b} + (1-p)\right)^{n-1},$$

$$a'_2 = (1-p)^{n-1},$$

$$a'_3 = 2 \left(1 - \left(1 - \frac{2}{x_1}\right)p\right)^{n-1} - \left(1 - \left(1 - \frac{2}{x_2}\right)p\right)^{n-1}.$$

Combining (3-24) and (3-25), the following theorem can be formulated.

Theorem 3.3: Given a capture ratio b , the network size n and a fixed power investment in terms of transmission probability p , the power investment of each node can be minimized using the adaptive CSI method when the SNR satisfies both (3-24) and (3-25). When $SNR \leq t_l(b, n, p)$, the threshold-based CSI method is more power-efficient than the others. When $SNR \geq t_h(b, n, p)$, a node should use no-CSI method for power efficiency. $\square$

It should be noted that the intersection of (3-24) and (3-25) may be an empty SNR set for a given (b, n, p) . It means that under such circumstances, either no-CSI or threshold-based CSI is superior to the others.

As an illustrative example, Figure 3-2 shows the throughputs of the three methods for a given power investment (i.e., transmission probability) $p = 0.05$ and $n = 10$. Figure 3-2 shows that using the adaptive CSI, the power investment can be minimized for a wide variety of systems with different SNRs and capture ratios. For this particular example, the power reduction can go up to 9.3%. Figure 3-3 traverses through all the

possible power investment schemes, it can be found that the power reduction can go up to 12.3%.

Figure 3-2 Throughput Comparison for a Given Transmission Probability $p=0.05$

Figure 3-3 Power Reduction for different Power Investment Schemes

3.6 Convergence Analysis

3.6.1 ACK-based Game Strategy

In Section 3.3, the Nash equilibrium is derived for the adaptive CSI method. In this section, an ACK-based algorithm is proposed for each node to find the power-efficient Nash equilibrium in a distributed manner.

Each node i in the network updates the transmission probability p_i synchronously every I time slots and each node transmits with this probability for the current update interval. For node i , the new transmission probability for the $t+I$ -th update is determined by

$$p_i^{(t+1)} = \frac{\rho_i}{p_{\text{PSR}_i}^{(t)}} \quad (3-26)$$

where $p_{\text{PSR}_i}^{(t)}$ is the packet success rate for node i from the t -th update to the $t+1$ -th update (the t -th update interval). $p_{\text{PSR}_i}^{(t)}$ can be obtained from ACK information.

In particular, the initial transmission probability $p_i^{(1)}$ can be any value smaller than the Nash equilibrium point. In practice, each node can start with $p_i^{(1)} = \rho_i$ for simplicity and fast convergence.

The following theorem shows each node will converge to the Nash equilibrium using the strategy in (3-26). It is assumed that the throughput demand profile $\boldsymbol{\rho}$ is feasible.

Theorem 3.4: Using the ACK-based strategy in (3-26), the transmission probability of each node in the network asymptotically converges to the power-efficient Nash equilibrium point of the game (3-3).

Proof. Case 1: First consider the case where the number of nodes in the network is fixed. For this scenario, the following should be satisfied:

- i) The sequence of the transmission probability of any node i $(p_i^{(1)}, p_i^{(2)}, \dots, p_i^{(t)}, p_i^{(t+1)})$ is increasing;
- ii) Any two arbitrary entries p_i and p_k in the transmission probability vector $\boldsymbol{p}$ asymptotically follow $p_i/p_k = (\rho_i/p_{\text{PSR}_i})/(\rho_k/p_{\text{PSR}_k})$ regardless of their initial values;
- iii) The actual throughput of node i at any update interval t will not exceed its corresponding throughput demand.

Factor i) must be satisfied because only when the sequence of the transmission probability increases then it is possible that it converges to the equilibrium point.

Factor ii) must be met because at the equilibrium point, according to (3-9) and *Corollary 3.1*, $\rho_i/\rho_k = (p_i p_{\text{PSR}_i})/(p_k p_{\text{PSR}_k})$ and thus factor ii) must follow. Factor iii) guarantees that the transmission probability will not go to the region where the actual throughput is larger than what is required and thus it can avoid converging to the unfavorable energy-inefficient equilibrium point.

While factor ii) immediately follows from the game strategy and *Corollary 3.1*, and it can be met starting from the second update, factor i) can be proved by induction. It has been assumed that $p_i^{(1)}$ is no greater than ρ_i . Thus, $p_i^{(2)} = \rho/p_{\text{PSR}_i}^{(1)} > p_i^{(1)}$. Assume that $p_i^{(2)} < p_i^{(3)} < \dots < p_i^{(t-1)} < p_i^{(t)}$, one needs to prove that $p_i^{(t)} < p_i^{(t+1)}$ holds.

Recall that p_{PSR_i} is a decreasing function of p_j , $\forall p_j \in \mathbf{p}_{-i}$. As $p_j^{(t-1)} < p_j^{(t)}$, $p_{\text{PSR}_i}^{(t)} > p_{\text{PSR}_i}^{(t+1)}$, it thus follows that $p_i^{(t)} < p_i^{(t+1)}$.

As for the proof of iii), since $p_{\text{PSR}_i}^{(t+1)} < p_{\text{PSR}_i}^{(t)}$, it follows that $r_i^{(t+1)} = p_i^{(t+1)} p_{\text{PSR}_i}^{(t+1)} < p_i^{(t+1)} p_{\text{PSR}_i}^{(t)}$. Thus $r_i^{(t+1)} < \rho_i$ according to (3-26).

Combining factor i) and factor iii), the transmission probability p_i of node i will increase monotonically and is always smaller (yet getting closer) to the equilibrium point. Meanwhile, factor ii) ensures that for each update p_i and the transmission probability of any other node k will “move” up in an appropriate step and thus they asymptotically converge to the equilibrium point at the same time.

Case 2: Next consider the case when there are newly-joined nodes during the network operation. In this case, a new equilibrium point must be sought and the new equilibrium probability is expected to be greater than the previous one as more packet transmissions are expected. This situation can be

viewed as a special case of case 1. The convergence can be achieved as long as the new throughput demand is feasible.

Case 3: Finally the case where there are nodes dissociating from the network or stop transmitting data during the network operation is examined. Contrary to case 2, the new equilibrium probability of each node should be smaller than the previous one as there is less traffic in the network. For this case, which is similar to case 1, the following requirements must be met:

- i) The sequence of the transmission probability of any node i decreases over time after the nodes leave the network;
- ii) Any two arbitrary entries p_i and p_k in the transmission probability vector $\mathbf{p}$ asymptotically follow $\rho_i/\rho_k = (p_i p_{\text{PSR}_i})/(p_k p_{\text{PSR}_k})$ regardless of their values at the time the nodes leave the network;

The rationales and proofs are similar to case 1 and omitted for brevity. In this case, p_i will decrease. Thus it will not converge to the energy-inefficient equilibrium point, which is always greater than the value of p_i at the time the nodes leave the network.

This completes the proof of *Theorem 3.4*.

Remark 3.1: This proposed ACK-based updating strategy can also apply to threshold-based CSI and no-CSI methods. The proofs are very similar and are omitted.

Remark 3.2: Through simulations, it is observed that the condition that the initial transmission probability $p_i^{(1)}$ should be any value smaller than the Nash equilibrium point can be relaxed. Even for initial transmission probabilities greater than the equilibrium point, each node can still adjust the probability to the optimum using the

proposed algorithm. The simulations also show that the transmission probability vector can always converge to the equilibrium point with negligible errors within 3 updates.

3.6.2 Update Interval Analysis

For the proposed algorithm, the update interval I is a key parameter that can affect its performance. There exists a trade-off: frequent updates allow each node to respond promptly to the traffic condition. However, a short update interval may result in a high randomness in calculating the p_{PSR} and thus the transmission probability of each node may deviate from the optimal point.

A statistical characterization of the packet transmission is given here in order to provide a guideline on choosing the update interval that allows timely update while reducing the randomness to a desired level.

Each packet transmission is considered *i.i.d* with success probability p_{PSR} , where p_{PSR} can be obtained from (3-10). In other words, each packet transmission can be seen as a Bernoulli trial. If we take m consecutive transmissions, the number of successes out of m transmissions follows binomial distribution $B(m, p_{PSR})$. Furthermore, when $mp_{PSR} > 5$ and $m(1 - p_{PSR}) > 5$, the binomial distribution can be approximated using the corresponding normal distribution $N(mp_{PSR}, mp(1 - p_{PSR}))$ [87].

Accordingly, the p_{PSR} for m consecutive transmissions is also a random variable following normal distribution $N(p_{PSR}, p_{PSR}(1 - p_{PSR})/m)$. Denote each set of m consecutive transmissions as a minimal unit. For w consecutive minimal units, the sample mean of PSR is also approximately normally distributed with mean $\bar{x} = p_{PSR}$ and standard deviation $\sigma = \sqrt{p_{PSR}(1 - p_{PSR})/mw}$.

The standard deviation of the sample mean σ can be used to characterize the significance of the randomness and show how “steady” is the p_{PSR} obtained. It can be shown that a larger w , which translates to a larger update interval, will bring about smaller standard deviation of the p_{PSR} and *vice versa*.

Given a standard deviation requirement, say T , the minimal sample size w_{opt} can be readily computed as $w_{\text{opt}} = p_{\text{PSR}}(1 - p_{\text{PSR}})/mT^2$. Subsequently, as the update interval $I = mw/p_i$, the optimal update interval can be computed as $I_{\text{opt}} = \lceil p_{\text{PSR}}(1 - p_{\text{PSR}})/T^2 p_i \rceil = \lceil p_{\text{PSR}}(1 - p_{\text{PSR}})/T^2 \rho_i \rceil$.

It can be concluded that if the imposed standard deviation requirement is the same for every node, the node with the lowest throughput, say node i , will require the largest update interval. Assume that all nodes update their transmission probabilities synchronously, the update interval will depend on node i , i.e.,

$$I_{\text{net}} = \left\lceil \frac{p_{\text{PSR}}^2(1 - p_{\text{PSR}})}{T^2 \rho_i} \right\rceil \quad (3-27)$$

Determining the update interval online in an adaptive manner will theoretically lead to optimal results. By doing this, however, node i will have to broadcast the new update interval to the rest, which introduces additional traffic overheads and more power investment. Alternatively, the update interval can be fixed offline assuming the worst-case scenario that $p_{\text{PSR}}^2(1 - p_{\text{PSR}})$ is maximum. It can be shown that when $p_{\text{PSR}} = 2/3$, $p_{\text{PSR}}^2(1 - p_{\text{PSR}})$ is at its peak $4/27$. As such, (3-27) can then be approximated as

$$I_{\text{net}} \approx \left\lceil \frac{4}{27T^2 \rho_i} \right\rceil \quad (3-28)$$

3.7 Simulation Results

In this section, various Monte Carlo simulation results are presented to validate the proposed distributed convergence algorithm. A scenario where there are n nodes transmitting fixed-length packets to a base station in a probabilistic manner is considered. It is assumed that each transmission takes up one time slot with the possible acknowledgement. The update interval is determined using (3-28) with a standard deviation requirement of 0.04.

The applicability of the convergence algorithm for different CSI-based methods is first evaluated. In this case the capture ratio is $b = 3$ and the SNR is 10. The network size is $n = 10$. The convergence algorithm is used for all the three methods. Different throughput demands ranging from 0.005 per node to 0.04 per node have been evaluated. Each set of simulation is run for 10 times and the transmission probability of each node at equilibrium is recorded.

Figure 3-4 Comparisons between the Simulation Results and the Theoretical Analysis

(Sim: simulations; Anal: analytical derivations)

Figure 3-4 shows the actual throughput and transmission probability of both the simulation and the theoretical analysis. The simulation results match quite well with the theoretical ones for all the three methods, indicating that the proposed ACK-based convergence algorithm can achieve accurate results.

Figure 3-5 examines the accuracy of the convergence algorithm for different heterogeneous networks in detail. Such a network consists of 5 classes of nodes, with a throughput demand of 0.002, 0.004, 0.006, 0.008, 0.01 respectively. The capture ratio is $b = 5$ and the SNR is 50. Simulations have been conducted for the networks with different number of nodes per class, ranging from 1 to 4. Each set of simulation is repeated 10 times. It can be shown that the nodes are able to meet the throughput demand regardless of the number of nodes in the network, with only an average error

of 1.1% and a standard deviation of no more than 0.1% of its throughput demand. The transmission probability increases as the number of nodes increases. This is because more frequent transmissions are needed to compensate for the higher packet loss rate due to the increment of the number of nodes in the network.

Figure 3-5 Throughput and Transmission Probability for Heterogeneous Networks (□: transmission probability; Δ: actual throughput; *: throughput demand)

As an illustrative example, Figure 3-6 presents the convergence speed for a heterogeneous network with 5 nodes and a capture ratio of 5 and a SNR of 50. The throughput demand is set to be 0.01, 0.02, 0.03, 0.04, 0.05 for each node respectively. It is observed that each node can reach the equilibrium point from the 3rd update instant and is stable subsequently with negligible deviations after 2 updates.

Figure 3-6 Performance of the Convergence Algorithm (Node 1: ----; Node 2: ----;
Node 3: ----; Node 4: ----; Node 5: ----)

Lastly, the robustness of the algorithm against changes on the number of nodes in the network is examined. The capture ratio and the SNR are the same as in the previous simulations. In the following study 10 nodes are evaluated, each with a throughput demand of $0.001i$, where i is the node ID labeled from 1 to 10. In Phase I (from 1st to 7th update intervals), only the first 5 nodes transmit packets. In Phase II (from 7th to 10th update intervals), two more nodes namely Node 6 and Node 7 are active in the network. In Phase III (from 10th to 13th update intervals), all nodes actively perform transmissions. In Phase IV, Nodes 6-10 leave the network while Nodes 1-5 remain active in the network.

Figure 3-7 Transmission Probability with Changes on the Number of Nodes

Figure 3-7 plots the transmission probability versus the update interval. It can be observed that both groups of nodes adapt well with the changes and the new equilibrium points can be re-established in a distributed manner. Table 3-1 shows the actual throughput at the equilibrium. It is assumed that the equilibrium can be established one update interval later after each change in the number of nodes. The results show that each node matches well with its corresponding throughput demand, with an average relative error of 1.26%. Compared with the case where there is no change in the number of nodes (i.e., Figure 3-5, with an average error of 1.1%), the error is still insignificant, indicating that the proposed algorithm works well with such changes.

Table 3-1 Actual Throughput with Changes on the Number of Nodes

Node	Actual Throughput	Relative Error (%)
1	0.000977	-2.28
2	0.002002	0.113
3	0.003128	4.25
4	0.004033	0.826
5	0.004906	-1.88
6	0.006056	0.933
7	0.006973	-0.389
8	0.008054	0.680
9	0.009002	0.0178
10	0.010336	3.36

3.8 Summary

In this chapter, a new method to exploit the channel state information (CSI) in an ALOHA network named adaptive CSI has been presented. The throughput performance of the proposed adaptive CSI method has been analyzed and compared with the threshold-based CSI and the no-CSI method. It is shown that the proposed method is able to achieve up to 9.9% throughput improvement and 12.3% power reduction for a wide variety of systems as compared to the other two approaches. Two guidelines have been derived on selecting of these three methods under different system scenarios. The proposed method can be readily implemented in a distributed manner with the use of the acknowledgement packets issued by the base station. Both the analytical and simulation results show that this distributed implementation is able to guarantee fast convergence and is robust against changes in the number of nodes in the network.

Two types of local information, namely the channel state information (CSI) and acknowledgment packet (ACK), are used in the proposed method. The CSI provides information on the channel scattering, attenuation and fading. Based on CSI, each node is able to determine its own transmission strategy in a better way. The ACK is a reflection of both channel condition and other nodes' channel utilization. These two types of local information provide a complete characterization of a Rayleigh-fading ALOHA network. By choosing among different transmission strategies based on the local information, each user in the network is able to achieve the best throughput performance.

However, these two types of information may be neither available nor necessary for a wide variety of distributed networks. For short-range communication, packet collision is the dominant factor of transmission failure and channel fading is normally not a serious issue. As such, CSI is not helpful. For data-driven applications such as file uploading, the network usually provides a best-effort service and no acknowledgement packet is implemented. In such cases, novel methods to exploit other types of local information must be developed. In the next chapter, it is shown how traffic estimation can be performed without the use of these two types of local information. The use of clear channel assessment information, which is always available in CSMA networks, is explored.

4. Real-time Distributed Traffic Estimation in CSMA Networks

4.1 Introduction

In Chapter 3, the transmission probability control in a fading ALOHA network has been investigated. Given a specific channel condition, the transmission probability of each node uniquely determines the network performance. In a CSMA network, it is much more complicated because several factors such as the contention window size, backoff process may all contribute to the performance. In order to optimize the throughput performance in a CSMA network, each node first needs to properly model the network and estimate the network traffic in a distributed manner. In a distributed IEEE 802.15.4 CSMA network, it is important for each node to accurately estimate the on-going network traffic. Knowing others' traffic is useful in many applications. For example, in a wireless network control system [55], a sensor node needs to determine its sampling period based on the traffic intensity: heavier traffic indicate more packet loss and smaller sampling periods are required to compensate for the loss and to stabilize the control system. In a general CSMA network, each node can determine its best transmission strategy to optimize the throughput performance only if other nodes' strategies are well known. This chapter presents two real-time traffic estimation algorithms for two different types of heterogeneous IEEE 802.15.4 CSMA networks.

In Chapter 2, the modeling techniques and traffic characterization has been described. As mentioned, models of both the homogeneous and heterogeneous CSMA networks have been developed and network performance metrics can be derived from such models. However, solving the models require sophisticated numerical methods and are

computationally expensive. It is thus inapplicable for distributed computing in sensor nodes. Moreover, change detection must also be developed so as to capture the traffic intensity in real time as network traffic may change over time.

The algorithms proposed in this chapter aim to overcome the above weaknesses. Specifically, the proposed real-time distributed traffic estimation methods based on a discrete Markov chain model have the following advantages:

- The proposed algorithms enable each participating node to characterize the ongoing traffic in a distributed manner as opposed to a centralized modeling method.
- The proposed algorithms require no central coordination and as a result, no communication overhead is needed for the execution of the algorithms. Moreover, they can naturally detect the traffic changes in the network.
- The proposed algorithms have much less computational complexity as compared with a centralized multi-dimensional Markov chain model and can be easily discretized and stored in a look-up table for fast estimation.

4.2 Preliminaries and Problem Formulation

4.2.1 An Overview of IEEE 802.15.4 CSMA/CA

In this section, a brief overview of the IEEE 802.15.4 CSMA/CA protocol is provided, focusing on the details that are related to the proposed study. A more comprehensive introduction can be found in [88].

The 802.15.4 is part of the IEEE family of standards that defines the physical layer and the medium access control layer (MAC) for wireless personal area networks (WPAN). It is intended for devices with low data rate, low complexity and stringent power

requirement. The raw data rate in industrial, scientific and medical (ISM) band is 250 kbps. The basic time unit “slot” is defined as the unit backoff period which contains 10 bytes. In the time-slotted beacon-enabled mode, a superframe structure is used to govern the packet transmission. Each superframe begins with a beacon sent by the coordinator, followed by an active portion and an optional inactive portion. The active portion consists of a contention-access part and an optional contention-free part.

This thesis considers the slotted CSMA in the contention access portion. In a slotted CSMA network, a node trying to transmit a packet would first initialize the counter called the number of backoffs (NB). Then the node performs the backoff algorithm to delay for a random number of time slots which is uniformly distributed in the range of $[0, 2^{BE} - 1]$, where BE is the backoff exponent. When the backoff period is over, the node performs a clear channel assessment (CCA) to detect whether the channel is idle. The node would begin to transmit data if two consecutive CCAs are idle. Otherwise, the node would increase the NB and BE by one, without exceeding the maximum backoff limit m and maximum backoff exponent m_b respectively. The packet will be discarded if NB exceeds m . Otherwise, the node will start to transmit a packet after performing two CCAs to confirm that the channel is idle. An ACK would indicate successful transmission. If the node fails to receive ACK due to collision or ACK timeout, the packet will be considered a failure assuming that no retransmission mechanism is implemented.

4.2.2 Problem Formulation

Consider a generic single-hop network where N nodes contend to transmit packets to a central node (i.e., the coordinator) using the IEEE 802.15.4 slotted CSMA protocol. It is assumed in this thesis that the packet loss due to MAC layer contention dominates

other forms of packet loss such as path loss and channel fading. This assumption is reasonable as for most applications that operate in close proximity, packet loss on physical layer is usually negligible [34, 89]. Furthermore, it is assumed that there is no hidden terminals for any arbitrary node in the network.

Assume node i has a transmission rate of $1/\lambda_i$ (e.g., $\lambda_i = 100$ means node i on average initializes a new packet transmission every 100 slots) and assume that λ_i can be arbitrary tuned to meet the throughput demand. This feature applies to a wide variety of wireless industrial network systems [90-92]. For example, the transmission rate of network control systems employing data rate theorem [93] needs to be tuned frequently according to the channel condition to stabilize the control system. Another example is a model-based network control system [92], whereby the sensor packet generation needs to be tuned according to the dynamics of the control system. $1/\lambda_i$ can also be viewed as a probability that node i initializes a new packet transmission in a random time slot. Further assume that each packet from node i lasts for L_i slots and no retransmission is implemented on MAC layer (retransmission can be implemented on higher layer).

The problem to be tackled in this chapter can be broadly described as “establishing a function that relates traffic states to locally measurable variables”. Specifically, the following two scenarios are considered:

- For a network where all the packets are of the same length L , we attempt to devise an algorithm that enables an arbitrary node i to express the aggregate transmission rate of all other nodes $\sum_{j \neq i} (1/\lambda_j)$ as a function of the busy channel probability of node i .
- For a network where packet lengths are different, we attempt to develop an algorithm that enables an arbitrary node i to estimate all other nodes' aggregate

transmission rate of $\sum_{j \neq i}(1/\lambda_j)$ and their aggregate traffic loads $\sum_{j \neq i}(L_j/\lambda_j)$ based on the busy channel probability and the packet success rate.

4.3 Markov Chain Channel-State Modeling

In order to model the interactions in the network, it is essential to characterize the relationship between the two parameters of node i , namely the probability that node i starts to perform a CCA session in a random time slot α_i and the probability that the CCA result is busy, namely busy channel probability β_i . Note that each CCA session may take up one or two slots, depending on whether the first one is busy or not. As for β_i , it is the probability that the sensing node finds the channel busy in its first CCA or in the second CCA given the first one is idle. Due to the sharing nature of the network, each packet is bound to experience more than one CCA session. Thus, $\alpha_i > 1/\lambda_i$. The exact number of CCA sessions within each packet depends on how busy the channel is. Higher β_i indicates that a node will on average perform more backoffs for a certain packet and thus higher α_i , and *vice versa*. This relationship can be quantified by calculating the average number of CCA sessions that node i experiences for each packet as follows [32]:

$$\alpha_i = \left(\sum_{k=0}^{m-1} (k+1)(1-\beta_i)\beta_i^k + (m+1)\beta_i^m \right) / \lambda_i = \frac{1-\beta_i^{m+1}}{(1-\beta_i)\lambda_i} \quad (4-1)$$

where $\sum_{k=0}^{m-1} (k+1)(1-\beta_i)\beta_i^k + (m+1)\beta_i^m$ enumerates all the possible number of CCA session for each packet and their corresponding probabilities. Furthermore, β_i also depends on every other node's probability of starting to perform CCA sessions in a random time slot α_j . This relationship can be characterized by the channel state model in Figure 4-1.

Figure 4-1 Heterogeneous Channel State Model of an Arbitrary Node i

The idea of the channel state model lies in the property of the CSMA that a node needs to sense two successive idle slots before transmitting a packet. The channel state model is thus constructed to figure out what is the probability that a random adjacent slot-pair is idle. As such, the slotted channel is modeled as a discrete Markov chain whose states, namely idle-idle, idle-busy, busy-idle, busy-busy, are on an adjacent slot-pair basis [32].

Each node i has a unique channel state model, which reflects the traffic of all other nodes. Figure 4-1 describes an arbitrary node i 's model, where α_j is the probability that any node $j \neq i$ initializes a CCA in a random slot and $p_i^1 = \left(\frac{\sum_{j \neq i} \alpha_j L_j}{\sum_{j \neq i} \alpha_j} - 2 \right) / \left(\frac{\sum_{j \neq i} \alpha_j L_j}{\sum_{j \neq i} \alpha_j} - 1 \right)$ refers to the probability that the channel remains in busy-busy state.

The model is simply based on the property of CSMA/CA that a node needs to sense 2 successive idle slots before a packet transmission. Each state in the discrete Markov chain is on an adjacent slot-pair basis. $\tau_i = 1 - \prod_{j \neq i} (1 - \alpha_j)$ denotes the probability that at least one node other than i performs a packet transmission and the state consequently goes from idle-idle to idle-busy. If none of the nodes initializes a transmission at a particular time slot, the state remains idle-idle. When a transmission is initialized, the state inevitably goes to idle-busy and subsequently busy-busy as each packet is assumed to last more than one slot. The probability that the state goes from busy-busy to busy-idle, i.e., p^1_i in Figure 4-1, depends on the average packet length $\bar{L} = \sum_{j \neq i} \alpha_j L_j / \sum_{j \neq i} \alpha_j$. When a packet transmission is completed and the state turns to busy-idle, it will jump to idle-idle in the next time slot. Summarizing the state transitions, the stationary channel state can be solved as $P_{II}^i = 1 / (1 + \tau_i(1 + \bar{L}))$, $P_{BB}^i = (\bar{L} - 1)\tau_i / (1 + \tau_i(1 + \bar{L}))$ and $P_{IB}^i = P_{BI}^i = \tau_i / (1 + \tau_i(1 + \bar{L}))$, where P_{II}^i , P_{BB}^i , P_{IB}^i and P_{BI}^i are the probabilities of node i that the slot-pair state is in idle-idle, busy-busy, idle-busy and busy-idle respectively.

For node i , the channel is busy when the state is not P_{II}^i . Thus, the busy channel probability is determined as

$$\beta_i = 1 - \frac{1}{1 + \tau_i(1 + \bar{L})} \quad (4-2)$$

With (4-1) and $\bar{L} = \sum_{j \neq i} \alpha_j L_j / \sum_{j \neq i} \alpha_j$, (4-2) can be written as

$$\beta_i = 1 - \frac{1}{1 + (1 - \prod_{j \neq i} (1 - \frac{(1 - \beta_j^{m+1})}{(1 - \beta_j) \lambda_j})) (1 + \frac{\sum_{j \neq i} \frac{(1 - \beta_j^{m+1}) L_j}{(1 - \beta_j) \lambda_j}}{\sum_{j \neq i} \frac{(1 - \beta_j^{m+1})}{(1 - \beta_j) \lambda_j}})} \quad (4-3)$$

The difference from the work in [32] is that instead of viewing the channel state as a whole, we model the channel from the perspective of an arbitrary node i . Each node has a unique channel state model. This slight yet important modification allows us to characterize the channel states in a distributed manner.

4.4 Traffic Estimation of CSMA Networks with Constant Packet Length

4.4.1 Traffic Estimation

In this section, it is assumed that every packet in the network has the same length L . In this case, β_i given in (4-3) is reduced to

$$\beta_i = 1 - \frac{1}{1 + \tau_i(1+L)} = \frac{(1 - \prod_{j \neq i}(1 - \alpha_j))(1+L)}{1 + (1 - \prod_{j \neq i}(1 - \alpha_j))(1+L)} \quad (4-4)$$

In practice, β_i can be measured by collecting the clear channel assessment (CCA) results. Once β_i is known, τ_i can be determined as:

$$\tau_i = 1 - \prod_{j \neq i}(1 - \alpha_j) = \frac{\beta_i}{(1 - \beta_i)(1+L)} \quad (4-5)$$

The term $\prod_{j \neq i}(1 - \alpha_j)$ contains transmission rate information of all other nodes $j \neq i$ and can be rewritten using (4-1) as:

$$\prod_{j \neq i}(1 - \alpha_j) = \prod_{j \neq i}(1 - \frac{1 - \beta_j^{m+1}}{(1 - \beta_j)\lambda_j}) \quad (4-6)$$

One important observation is that for any 2 arbitrary node i and r , the backoff failure probability β_i and β_r are almost equal as long as the network size is not too small, or when the nodes are of homogeneous nature. This is because β_i and β_r are determined by $\prod_{j \neq i}(1 - \alpha_j)$ and $\prod_{j \neq r}(1 - \alpha_j)$ respectively and the ratio $\prod_{j \neq i}(1 - \alpha_j) / \prod_{j \neq r}(1 - \alpha_j) = (1 - \alpha_r) / (1 - \alpha_i)$ is very close to 1 as α_r and α_i are

typically smaller than 0.01 [55, 90]. Thus the subscript i for every β_i can be dropped without affecting the analysis. Combining (4-5) and (4-6), one can get:

$$\beta = \frac{(1 - \prod_{j \neq i} (1 - \frac{1 - \beta^{m+1}}{1 - \beta} \frac{1}{\lambda_j})) (1 + L)}{1 + (1 - \prod_{j \neq i} (1 - \frac{1 - \beta^{m+1}}{1 - \beta} \frac{1}{\lambda_j})) (1 + L)} \quad (4-7)$$

Our interest lies in finding a detailed characterization of the aggregate transmission rate $\sum_{j \neq i} (1/\lambda_j)$ for $\forall j \neq i$. However, it cannot be directly derived from (4-7). Notice that in (4-6), every $(1 - \beta^{m+1})/\lambda_j(1 - \beta)$ is sufficiently small (typically far smaller than 0.01 for non-saturated applications [55, 90]) and when expanding the polynomial $(1 - \prod_{j \neq i} (1 - (1 - \beta^{m+1})/\lambda_j(1 - \beta)))$, the second and higher order terms can be neglected without compromising the accuracy (e.g., the error when $(1 - \beta^{m+1})/\lambda_j(1 - \beta) = 0.01$ and $N = 10$ is less than 0.005). As such, (4-7) can be rewritten in order to “isolate” λ_j from other variables as follows:

$$\beta \approx \frac{\frac{1 - \beta^{m+1}}{1 - \beta} \sum_{j \neq i} (1/\lambda_j) (1 + L)}{1 + \frac{1 - \beta^{m+1}}{1 - \beta} \sum_{j \neq i} (1/\lambda_j) (1 + L)} \quad (4-8)$$

From (4-8), $\sum_{j \neq i} (1/\lambda_j)$ can be given as:

$$\sum_{j \neq i} (1/\lambda_j) = g(\beta) = \frac{\beta}{(1 - \beta^{m+1})(1 + L)} \quad (4-9)$$

4.4.2 Detectability Analysis

Using (4-9), each node can obtain an estimate of $\sum_{j \neq i} (1/\lambda_j)$ from the measurements of busy channel probability β . There are two outstanding issues that need to be resolved before applying (4-9). First, can a change on $\sum_{j \neq i} (1/\lambda_j)$ be detected from β ? Second,

β itself is also subject to randomness. Can each node differentiate between the change in $\sum_{j \neq i}(1/\lambda_j)$ and the random deviation of β ?

An arbitrary node i can detect changes in the traffic (e.g., change on the number of active nodes) when there is a significant increase or decrease on β . The sensitivity of this detection mechanism is first analyzed. Any change in the number of nodes will first affect the value of $\sum_{j \neq i}(1/\lambda_i)$. The sensitivity of β in terms of $\sum_{j \neq i}(1/\lambda_i)$ can be derived by finding the derivative of $\beta = g^{-1}(\sum_{j \neq i}(1/t_j))$. Since the expression of $g^{-1}(\sum_{j \neq i}(1/t_j))$ can hardly be explicitly found, its inverse function $g(\beta)$ is instead analyzed. It can be shown that its derivative $g'(\beta) = (1 + m\beta^{m+1})/(1 - \beta^{m+1})^2(1 + L)$ is a monotonically decreasing function and when β is small, $g'(\beta)$ can be approximated as $g'(\beta) \approx 1/(1 + L)$. According to the property of the derivative of inverse function, the derivative of $g^{-1}(\sum_{j \neq i}(1/\lambda_i))$ is approximately $(1 + L)$ when β is small. When the busy channel probability is high, the slope of $g^{-1}(\sum_{j \neq i}(1/\lambda_i))$ will decrease significantly. Figure 4-2 shows the sensitivity of β *versus* the busy channel probability for different combinations of m and L . It is observed that when $\beta < 0.4$, the sensitivity is close to $1 + L$. It drops quickly when $\beta > 0.5$ and the sensitivity is close to 1 when $\beta = 0.8$. For control and monitoring applications, the traffic load is relatively low and β rarely exceeds 0.5. Thus, every unit of change in $\sum_{j \neq i}(1/t_j)$ will in general be amplified to around $1 + L$ units of change in β .

Figure 4-2 Sensitivity with respect to busy channel probability

Each node i obtains β by collecting the CCA information and as the backoff process in a CSMA network is random, the obtained β is also subject to randomness. The randomness may also result in fluctuations in β even when there is no change in the number of active nodes. Thus, it is necessary to quantify such fluctuations and evaluate its impact on the detection of traffic changes.

Each CCA can be considered an independently identically distributed (*i.i.d*) process with a mean busy channel probability $\bar{\beta}$. In other words, each CCA is a Bernoulli trial and when T CCAs are performed for a single update interval, the number of busy results follows binomial distribution $B(T, \bar{\beta})$. Furthermore, when $T\bar{\beta} > 5$ and $(1 - \bar{\beta}) > 5$, the binomial distribution can be approximated as the normal distribution $N(T\bar{\beta}, T\bar{\beta}(1 - \bar{\beta}))$ [87]. Thus, β also follows the normal distribution $N(\bar{\beta}, \bar{\beta}(1 - \bar{\beta})/T)$. Using a $\alpha\%$ confidence level, the fluctuation on β can be characterized by

$[\bar{\beta} - \epsilon\sigma \quad \bar{\beta} + \epsilon\sigma]$, where ϵ is the z-value corresponding to $\alpha\%$ and $\sigma = \sqrt{\bar{\beta}(1 - \bar{\beta})/T}$.

Combining the results of the sensitivity analysis and the fluctuation analysis, it can be concluded that the changes in the traffic, namely $\sum_{l \in \text{change}} (1/t_l)$, can be detected when the change in β caused by the traffic exceeds the maximal fluctuation on β . In other words, $\sum_{l \in \text{change}} (1/t_l)$ can be detected with $\alpha\%$ confidence if:

$$\sum_{l \in \text{change}} (1/t_l) \geq \frac{2\epsilon \sqrt{\frac{\bar{\beta}(1 - \bar{\beta})}{T}} (1 + m\bar{\beta}^{m+1})}{(1 - \bar{\beta}^{m+1})^2 (1 + L)} \quad (4-10)$$

In actual implementations, as $\bar{\beta}$ is unavailable, the measured β can be used to approximate $\bar{\beta}$. It is also more convenient to use the update interval I (sec) instead of T . They can be easily related as $I = T(1 - \bar{\beta})\lambda_i / (1 - \bar{\beta}^{m+1})RB_{\text{slot}}$, where R is the data rate (bps) at PHY layer and B_{slot} is the number of bits in a slot. Thus, (4-10) can be rewritten as:

$$\sum_{l \in \text{change}} (1/t_l) \geq \frac{2\epsilon \sqrt{\frac{\bar{\beta}(1 - \bar{\beta})^2 \lambda_i}{IRB_{\text{slot}}}} (1 + m\bar{\beta}^{m+1})}{(1 - \bar{\beta}^{m+1})^{5/2} (1 + L)} \quad (4-11)$$

As an illustrative example, Figure 4-3 shows the minimal detectable traffic changes for different system scenarios for a typical IEEE 802.15.4-compliant node with data rate of 250 kbps and time slot length of 80 bits. A 95% confidence level is used.

It can be shown that as β increases, the proposed detection mechanism becomes less sensitive to traffic changes. It can also be observed from (4-10) as well as Figure 4-3

that more sensitive detection can be obtained when (1) the packet length is longer; (2) when the transmission rate is higher or (3) when the update interval is longer.

Figure 4-3 Minimal detectable aggregate traffic change versus busy channel probability (TR: Transmission rate; UT: Update interval (s)).

Note that the minimal detectable aggregate traffic is also the upper bound of the error of traffic estimation. In actual implementations, the errors among different update intervals can be canceled and in the long run as the errors are unbiased, the achievability of the throughput demand will not be compromised.

4.5 Traffic Estimation of CSMA Networks with Varying Packet Lengths

4.5.1 Traffic Estimation

For networks with varying packet lengths, the same approximation can be made as in (4-7). As such, (4-3) can be reduced as:

$$\beta = 1 - \frac{1}{1 + (1 - \prod_{j \neq i} (1 - \frac{(1 - \beta^{m+1})}{(1 - \beta)\lambda_j})) (1 + \frac{\sum_{j \neq i} \frac{(1 - \beta^{m+1})L_j}{(1 - \beta)\lambda_j}}{\sum_{j \neq i} \frac{(1 - \beta^{m+1})}{(1 - \beta)\lambda_j}})} \quad (4-12)$$

Using algebraic operation, (4-12) can be further simplified as

$$\beta = 1 - \frac{1}{1 + (1 - \prod_{j \neq i} (1 - \frac{(1 - \beta^{m+1})}{(1 - \beta)\lambda_j})) (1 + \frac{\sum_{j \neq i} L_j / \lambda_j}{\sum_{j \neq i} 1 / \lambda_j})} \quad (4-13)$$

In addition to β , another measurable value of each node i is the packet success rate θ_i , which can be obtained from the ACK results. θ_i can be determined as [54]

$$\theta_i = (1 - \beta_i^{m+1}) \prod_{j \neq i} (1 - \alpha_j) \quad (4-14)$$

where $(1 - \beta_i^{m+1})$ is the probability that node i can find an idle channel for a particular packet and perform the transmission. $\prod_{j \neq i} (1 - \alpha_j)$ is the probability that when the packet from node i is being transmitted, none of other nodes perform the transmission at the same time. (4-14) can be simplified using the approximations in (4-13) as

$$\theta_i = (1 - \beta^{m+1}) \prod_{j \neq i} (1 - \frac{(1 - \beta^{m+1})}{(1 - \beta)\lambda_j}) \quad (4-15)$$

From (4-15), the $\prod_{j \neq i} (1 - (1 - \beta^{m+1}) / ((1 - \beta)\lambda_j))$ can be derived as

$$\prod_{j \neq i} \left(1 - \frac{(1 - \beta^{m+1})}{(1 - \beta)\lambda_j}\right) = \frac{\theta_i}{(1 - \beta^{m+1})} \quad (4-16)$$

Recall that one of the objectives in this proposed study is to derive the aggregate transmission rates of all other nodes $\sum_{j \neq i} 1/\lambda_j$. This can hardly be obtained from (4-13) and (4-15). Notice that from node i 's perspective, it cannot and does not have to determine which node the traffic come from. As such, node i can view the rest of the network as an aggregate traffic generator and it can be assumed that the aggregate traffic come equally from a fixed number of nodes n and fixed transmission rate $1/\lambda$, as shown in the following equation

$$\prod_{j \neq i} \left(1 - \frac{(1 - \beta^{m+1})}{(1 - \beta)\lambda_j}\right) \approx \left(1 - \frac{(1 - \beta^{m+1})}{(1 - \beta)} \frac{1}{\lambda}\right)^n \quad (4-17)$$

(4-17) can be established by finding a suitable pair of $(1/\lambda, n)$ such that the equation holds. Furthermore, according to the property of Binomial Series [87], when expanding the polynomial on both sides of the equation, the second and higher orders can be neglected without affecting the accuracy as long as $\frac{1}{\lambda}$ is small enough (e.g., $1/\lambda < 0.01$). Thus we have $\sum_{j \neq i} 1/\lambda_j \approx n/\lambda$. Note that for this approximation, smaller $1/\lambda$ yields higher accuracy. A practical approach to perform the approximation would be to fix a very small $1/\lambda$ and choose n such that (4-17) holds.

Thus, combined with (4-16), $\sum_{j \neq i} 1/\lambda_j$ is given as follows

$$\sum_{j \neq i} 1/\lambda_j \approx n/\lambda = \frac{n(1 - \beta)}{(1 - \beta^{m+1})} e^{\frac{\ln\left(\frac{\theta_i}{(1 - \beta^{m+1})}\right)}{n}} \quad (4-18)$$

Substituting (4-18) into (4-13), the aggregate traffic $\sum_{j \neq i} L_j/\lambda_j$ can be derived as

$$\sum_{j \neq i} L_j / \lambda_j = \frac{\beta \sum_{j \neq i} 1 / \lambda_j}{(1 - \beta) \left(1 - \frac{n(1 - \beta)}{(1 - \beta^{m+1})} e^{\frac{\ln\left(\frac{\theta_i}{(1 - \beta^{m+1})}\right)}{n}} \right)} - 1 \quad (4-19)$$

In what follows, the two measurements are denoted as $\mathbf{z}_i = (\beta, \theta_i)$. Also denote the traffic states as $\mathbf{x}_i = (\sum_{j \neq i} 1 / \lambda_j, \sum_{j \neq i} L_j / \lambda_j)$. (4-18) and (4-19) can be rewritten as

$$\mathbf{x}_i = F(\mathbf{z}_i) \quad (4-20)$$

Its inverse function can be also obtained using algebraic manipulations as

$$\mathbf{z}_i = F^{-1}(\mathbf{x}_i) \quad (4-21)$$

4.5.2 Moving Average Particle Filtering

In the last section, (4-20) provides an effective way to relate traffic states to local information. However, one outstanding issue is that the traffic information $\mathbf{z}_i = (\beta, \theta_i)$ obtained from the local information is a set of random variables, which may result in inaccurate estimation or require a long measurement interval to reduce the randomness. In this section, the characteristic of $\mathbf{z}_i$ is analyzed and an improved particle filtering techniques is proposed to achieve accurate estimation.

Statistical Framework

The network measurements β and θ_i are obtained from CCA and ACK results respectively for a certain time interval t and they can be defined as

$$\beta^t = \sum_{k=(t-1)B}^{tB-1} \frac{C_k}{B} \quad (4-22)$$

$$\theta_i^t = \sum_{k=(t-1)D}^{tD-1} \frac{E_k}{D} \quad (4-23)$$

where B and D are the number of CCAs and ACKs respectively during the time interval t . $C_k = 1$ if the CCA result is busy and $C_k = 0$ if otherwise. $E_k = 1$ if a packet from node i is successfully received by the receiver result is busy and $E_k = 0$ if otherwise.

It is observed that β^t approximately follows a normal distribution $N(\bar{\beta}, \bar{\beta}(1 - \bar{\beta})/B)$ with a mean value $\bar{\beta}$ and a variance $\bar{\beta}(1 - \bar{\beta})/B$. Similarly, θ_i^t also follows a normal distribution $N(\bar{\theta}_i, \bar{\theta}_i(1 - \bar{\theta}_i)/D)$ with a mean value $\bar{\theta}_i$ and a variance $\bar{\theta}_i(1 - \bar{\theta}_i)/D$. It is difficult to obtain the covariance of β^t and θ_i^t . For simplicity, it is assumed that the two variables are independent. Thus, the covariance can be approximated as

$$\text{cov}(\beta^t, \theta_i^t) \approx 0 \quad (4-24)$$

In general, the traffic state evolves as

$$\mathbf{x}_i^t = \mathbf{x}_i^{t-1} + \boldsymbol{\sigma}^t \quad (4-25)$$

where $\boldsymbol{\sigma}^t$ is an unknown random variable (referred to as *state noise*) which accounts for any traffic changes.

The measurements at time interval t can be expressed as

$$\mathbf{z}_i^t = F^{-1}(\mathbf{x}_i^t) + \boldsymbol{\varphi}^t \quad (4-26)$$

where $\boldsymbol{\varphi}^t$ is a 2-D normal random variable with zero mean for both entries and a covariance matrix $\mathbf{M} = \begin{bmatrix} \bar{\beta}(1 - \bar{\beta})/B & 0 \\ 0 & \bar{\theta}_i(1 - \bar{\theta}_i)/D \end{bmatrix}$. Since $\bar{\beta}$ and $\bar{\theta}_i$ are not available, the measured value can be used to approximate the covariance matrix as

$$\mathbf{M} \approx \begin{bmatrix} \frac{\beta_i^t(1 - \beta_i^t)}{B} & 0 \\ 0 & \frac{\theta_i^t(1 - \theta_i^t)}{D} \end{bmatrix} \quad (4-27)$$

In summary, (4-25)--(4-27) provide a complete description of the state model for the traffic estimation problem under consideration.

Autoregressive Moving Average Particle Filter

Particle filter [94] is a Monte Carlo method for Bayesian estimation. It has been widely used in a variety of applications such as object tracking [94] and visual tracking [95]. However, the basic particle filtering framework does not perform very well for the problem at hand. This is mainly because in (4-27), in the presence of σ^t , the traffic dynamics may change without following any statistical distribution and a conventional particle filter is unable to track the states accurately and promptly. In this section, an improved filtering technique called autoregressive moving average particle filter (ARMA-PF) is proposed. The basic idea of ARMA-PF is to combine a particle filter with an autoregressive moving average filter as in [27] when evaluating the weight of each particle. The details of ARMA-PF are described as follows.

Initially a number of particles, $\text{Par}^1 = \{\mathbf{x}_i^1(k), \omega_i^1(k)\}, k = 1, 2, \dots, K$, are generated where $\mathbf{x}_i^1(k)$ represents a candidate of $\mathbf{x}_i^t$ at $t = 1$ and its corresponding weight $\omega_i^1(k)$. The basic idea behind the particle filter is to recursively update the particles to obtain a Bayesian estimate of the posterior distribution $p(\mathbf{x}_i^t | \mathbf{z}_i^t)$. For each time interval, each particle will first be updated using (4-25). Then the weight of each particle based on the current measurement $\mathbf{z}_i^t$ and (4-27) is evaluated and normalized. This weight is then smoothed with the previous weight $\omega_i^{t-1}(k)$ using a smoothing factor α .

Table 4-1: The Procedure of ARMA-PF

ARMA-PF($\text{Par}^{t-1}, \mathbf{z}_i^t$)

- 1: $\text{Par}^t = \emptyset$
- 2: **for** $k = 1$ to K **do**
- 3: sample $\mathbf{x}_i^t(k) = p(\mathbf{x}_i^t | \mathbf{x}_i^{t-1}(k))$
- 4: assign current weight $\omega_i^t(k) = p(\mathbf{z}_i^t | \mathbf{x}_i^t(k))$
- 5: **end for**
- 6: $S = \text{sum}(\omega_i^t)$
- 7: **for** $k = 1$ to K **do**
- 8: normalize the weights $\omega_i^t(k) = \omega_i^t(k)/S$
- 9: **end for**
- 10: **for** $k = 1$ to K **do**
- 11: average weighting $\omega_i^t(k) = \alpha \omega_i^t(k) + (1 - \alpha) \omega_i^{t-1}(k)$
- 12: $\overline{\text{Par}}^t = \overline{\text{Par}}^t + \{\mathbf{x}_i^t(k), \omega_i^t(k)\}$
- 13: **end for**
- 14: **return** Par^t

The weighted average of the particle set at time step t is then used as the Bayesian estimate

$$\overline{\mathbf{x}}_i^t = \sum_{k=1}^K \mathbf{x}_i^t(k) \omega_i^t(k) \quad (4-28)$$

The specialty of the ARMA-PF lies in 2 aspects: first, the sampling is only performed once in the initial phase due to the state transition in (4-25). The value for each particle remains unchanged during the estimation process. This is to accommodate for (4-25). It also requires the samples can “cover” the range of all possible traffic loads. Second, the weight of the particle is a combination of past and current measurements. This provides

a trade-off mechanism between tracking traffic changes and filtering out of measurement noises.

4.6 Simulation Results

4.6.1 Results with Constant Packet Length

The effectiveness of the proposed algorithm for a heterogeneous CSMA network with constant packet length has been validated through extensive simulations. A CSMA network consisting of 21 nodes (one of them as the “observer”) is considered. Nodes except the “observer” are divided into 4 groups. The simulation settings are listed in Table 4-2. T_{coef} is a coefficient indicating the traffic changes. During the simulation, T_{coef} will change over time every 10 update intervals.

Table 4-2 Simulation Settings for Traffic Estimation in CSMA networks

	Group 1	Group 2	Group 3	Group 4
Transmission Rate	$0.005T_{\text{coef}}$	$0.0025T_{\text{coef}}$	$0.00167T_{\text{coef}}$	$0.00125T_{\text{coef}}$
Nodes Per Group	5			
T_{coef}	alternating among 1, $\frac{4}{3}$, 2, 3.			
Packet Length (slots)	4			
Simulation Time (s)	500			
Update Interval (s)	10

Figure 4-4 Traffic Estimation using (4-9)

The traffic estimation results are shown in Figure 4-4. Each node collects the clear channel assessment results and uses (4-9) to estimate the on-going traffic. It is observed that the proposed algorithm is able to estimate the varying traffic conditions in the network with high accuracy. Specifically, higher accuracy is observed when the traffic is lighter.

Figure 4-5 Traffic Estimation with Different Traffic Types

As a summary, Figure 4-5 presents the results of traffic estimation for different levels of traffic intensities. The average estimation error is 10.02%. When the traffic is light (i.e., the busy channel probability is lower than 0.2), the estimation error is negligible.

4.6.2 Results with Varying Packet Lengths

For network with varying packet lengths, a CSMA network consisting of 21 (one of them as the “observer”) nodes transmitting packets to a central node is considered. The nodes are of heterogeneous nature, with various transmission rates from 0.0125 to 0.01 and various packet lengths from 4 to 6 slots. The simulation is run for 500s and the update interval is 10s.

Figure 4-6 Autoregressive Moving Average Particle Filter (Actual Traffic: ----; $\alpha =$
0.1: ---; $\alpha = 0.3$: ---; $\alpha = 0.5$: ---; $\alpha = 0.7$: ---; $\alpha = 0.9$: ---)

Figure 4-7 Autoregressive Moving Average Filter (Actual Traffic: ----; $\alpha =$
0.1: ---; $\alpha = 0.3$: ---; $\alpha = 0.5$: ---; $\alpha = 0.7$: ---; $\alpha = 0.95$: ---)

Figure 4-8 Extended Kalman Filter (Actual Traffic: ----; $\mathbf{Q} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$: ---; $\mathbf{Q} =$

$$\begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}: \text{---}; \mathbf{Q} = \begin{bmatrix} 0.001 & 0 \\ 0 & 0.001 \end{bmatrix}: \text{---})$$

Figure 4-6 shows the estimation results of ARMA-PF with different smoothing factors compared with the actual traffic states. The number of particles in this case is 2000. It can be observed that the particle filter is able to track the states with small errors and the changes in the smoothing factor do not play a significant role in estimating the results. Figure 4-7 shows the estimation results of a generic autoregressive moving average filter [27], where the smoothing factor α is imposed on the measurement of the current update interval and $1 - \alpha$ is imposed on the past measurements. Figure 4-8 shows the results of an extended Kalman filter [27, 28], where $\mathbf{Q}$ refers to the covariance matrix of σ^t .

Table 4-3 Performance Comparisons of Different Tracking Algorithms

Algorithms	$\sum_{j \neq i} 1/\lambda_j$ Error (%)	$\sum_{j \neq i} L_j/\lambda_j$ Error (%)
ARMA $\alpha = 0$	51.2	18.9
ARMA $\alpha = 0.1$	50.7	19.0
ARMA $\alpha = 0.3$	49.6	19.7
ARMA $\alpha = 0.5$	48.1	21.0
ARMA $\alpha = 0.7$	45.0	24.0
ARMA $\alpha = 0.95$	33.4	38.7
EKF Q = 0	54.0	37.2
EKF Q = 0.1	64.3	47.5
EKF Q = 0.001	50.5	23.9
PF $\alpha = 0.1$	12.5	17.9
PF $\alpha = 0.3$	12.9	18.4
PF $\alpha = 0.5$	13.3	18.8
PF $\alpha = 0.7$	13.2	18.3
PF $\alpha = 0.9$	14.3	18.0

Table 4-3 presents the relative error of each algorithm on estimating the two traffic parameters. It can be observed that the proposed ARMA-PF exhibits highest accuracy among the 3 methods. Specifically, the relative error of the estimation of $\sum_{j \neq i} 1/\lambda_j$ is below 15% whereas the other two algorithms typically has a relative error of 30-60%. For the $\sum_{j \neq i} L_j/\lambda_j$, the relative error of ARMA-PF is about 18%, also less than the other two algorithms. Moreover, while the performance of the other two algorithms strongly depends on the choice of certain parameters, the proposed ARMA-PF is generally independent on the choice of the smoothing factor.

4.7 Summary

This chapter discusses the distributed traffic estimation in a CSMA network for two scenarios. The first one considers a network where nodes have different transmission rates but the same packet length. The second is a network whose nodes have different

transmission rates and packet lengths. For the first case, the aggregate transmission rate can be related to the busy channel probability using a channel-state Markov chain. The traffic estimation can be performed in a distributed manner by collecting the clear channel assessment result and calculating the busy channel probability. For the second case, the two parameters characterizing the network traffic named aggregate transmission rate and aggregate traffic loads can be related to two types of local information named busy channel probability and packet success rate. The traffic estimation can be performed by collecting the local information.

The traffic estimation is the first step towards throughput optimization. In the next chapter, a distributed throughput adjustment algorithm making use of the traffic estimation algorithm in this chapter is presented.

5. Adaptive Throughput Adjustment in CSMA Networks

5.1 Introduction

In Chapter 4, two distributed algorithms are proposed for estimating on-going heterogeneous traffic in an IEEE 802.15.4 CSMA network. One of the most important applications of the estimation algorithms is to determine the transmission rate to meet a specific demand (e.g., a pre-defined throughput requirement). This chapter presents an adaptive throughput adjustment algorithm for a heterogeneous CSMA network, which makes use of the estimation algorithm in Chapter 4. The objective of the proposed algorithm is to tune the transmission rate of each node to meet the specific performance requirements in a network with time-varying traffic. The proposed algorithm has the following advantages:

- Using the traffic estimation algorithm in Chapter 4, the adjustment algorithm is able to predict the packet success rate at equilibrium state and tune the transmission rate to meet the throughput demand. The algorithm is accurate with only an average error of 0.43% for homogeneous networks and 0.524% for heterogeneous networks.
- The algorithm is fully distributed and does not require any central coordination. Moreover, a change detection mechanism is also developed to allow each node to react promptly to on-going traffic changes and automatically adjust its transmission rate to meet the throughput demand.

5.2 Problem Formulation

The system scenario considered is the same as in Chapter 4, i.e., a generic single-hop network where N nodes contend to transmit packets to a central node (i.e., the coordinator) using the IEEE 802.15.4 slotted CSMA protocol. In the network, the node i has a transmission rate of $1/\lambda_i$ (e.g., $\lambda_i = 100$ means node i on average initialize a new packet transmission every 100 slots).

Each node i is assigned a throughput demand of $1/t_i$. For convenience, $1/t_i$ is defined as the ratio of the number of successful packets to the number of time slots during a certain time period, i.e., on average node i needs to successfully transmit a packet every t_i slots. Due to the backoff failure and packet collision, packet transmissions may fail and the packet success rate of node i p_{PSR_i} is smaller than 1. The objective of the proposed algorithm is for each node to find a suitable transmission rate $1/\lambda_i$ in a distributed manner such that:

$$\frac{p_{\text{PSR}_i}}{\lambda_i} = \frac{1}{t_i} \quad (5-1)$$

Denote the vector $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_N)$ for node 1 to N the optimal operating point where every node meets its throughput demand. It is assumed in this study that such a point always exists, i.e., the throughput demand is feasible. This assumption is reasonable in most sensor networks performing monitoring and control tasks as the data traffic generated by these nodes are usually below the capacity of the network. It is further assumed that the transmission rate of each node is updated simultaneously with a fixed update interval.

5.3 Distributed Rate Adjustment

Initially an arbitrary node i , with no prior information, tentatively transmits data at the rate $\lambda_i = t_i$. After a certain amount of time, node i can estimate the busy channel probability β_i by recording the CCA information. The estimation is performed by calculating the ratio of the number of busy CCAs to the number of all the CCA for a certain period and using this ratio as the busy channel probability β_i . β_i is then used to determine the optimal λ_i [33, 54].

The rate adjustment algorithm is based on the traffic estimation algorithm in Chapter 4. Recall that for a network where all packets are of the same length, the relationship between the aggregate transmission rate and the busy channel probability can be related according to (4-9) as

$$\sum_{j \neq i} (1/\lambda_j) = g(\beta) = \frac{\beta}{(1 - \beta^{m+1})(1 + L)} \quad (5-2)$$

As $\lambda_i = t_i$, we have $\sum_{j \neq i} (1/\lambda_j) = \sum_{j \neq i} (1/t_j)$. Once $\sum_{j \neq i} (1/t_j)$ is determined, estimation of the busy channel probability at the optimal operating point can be performed. In the following analysis, the superscript $*$ is used to denote variables at the optimal operating point. The optimal transmission rate for node i can be expressed as $1/\lambda_i^* = \Delta^*/t_i$, where Δ^* is the ratio of the optimal transmission rate $1/\lambda_i^*$ to $1/t_i$. According to the channel state model, when the transmission rate of node i is Δ^*/t_i , the busy channel probability and the transmission rates of node j for $\forall j \neq i$ can be related according to (4-7) as follows:

$$\beta^* = \frac{(1 - \prod_{j \neq i} (1 - \frac{1 - \beta^{*m+1}}{1 - \beta^*} \frac{\Delta^*}{t_j}))(1 + L)}{1 + (1 - \prod_{j \neq i} (1 - \frac{1 - \beta^{*m+1}}{1 - \beta^*} \frac{\Delta^*}{t_j}))(1 + L)} \quad (5-3)$$

Using the same approximation technique as in (4-8), (5-3) can be rewritten as:

$$\beta^* = \frac{\frac{1 - \beta^{*m+1}}{1 - \beta^*} \Delta^* \sum_{j \neq i} (1/t_j) (1 + L)}{1 + \frac{1 - \beta^{*m+1}}{1 - \beta^*} \Delta^* \sum_{j \neq i} (1/t_j) (1 + L)} \quad (5-4)$$

Solving (5-4) for Δ^* yields:

$$\Delta^* = \frac{\beta^*}{(1 - \beta^{*m+1}) \sum_{j \neq i} (1/t_j) (1 + L)} \quad (5-5)$$

In the meantime, Δ^* should satisfy $\Delta^* p_{PSR_i}^* = 1$ according to (5-1). The packet success rate $p_{PSR_i}^*$ of node i can be expressed as follows [65]:

$$p_{PSR_i}^* = (1 - \beta^{*m+1}) \prod_{j \neq i} (1 - \alpha_j^*) \quad (5-6)$$

where $(1 - \beta^{*m+1})$ is the probability that node i has access to an idle channel for a certain packet and $\prod_{j \neq i} (1 - \alpha_j^*)$ is the probability that at the same time there is no other node attempting to access the channel. Combining (5-1), (5-4) and (5-6), one can obtain:

$$(1 - \beta^{*m+1}) \left(1 - \frac{1 - \beta^{*m+1}}{1 - \beta^*} \Delta^* \sum_{j \neq i} (1/t_j) \right) = \frac{1}{\Delta^*} \quad (5-7)$$

The objective here is to estimate β^* from $\sum_{j \neq i} (1/t_j)$. As such, one can substitute (5-5) to (5-7) and eliminate Δ^* as follows:

$$\sum_{j \neq i} (1/t_j) = f(\beta^*) = \frac{\beta^* - 2\beta^{*2} - \beta^{*2}L + L\beta^*}{(1 + L)^2(1 - \beta^*)} \quad (5-8)$$

From (5-8), it can be shown that $\sum_{j \neq i}(1/t_j)$ is monotonically increasing in β^* when $0 < \beta^* < (L - (L + 2)^{1/2} + 2)/(L + 2)$ by differentiating $f(\beta^*)$. Thus, an inverse function $\beta^* = f^{-1}(\sum_{j \neq i}(1/t_j)) = h(\sum_{j \neq i}(1/t_j))$ exists in this region.

In conclusion, given the values of L , $\sum_{j \neq i}(1/t_j)$ and m , a unique β^* can be readily solved and so is Δ^* (using (5-5)). Node i can then use $\lambda_i^* = t_i/\Delta^*$ to determine its optimal transmission rate with respect to its throughput demand. In the actual implementation, the function $\beta^* = h(\sum_{j \neq i}(1/t_j))$ can be discretized and computed using numerical methods and stored in a look-up table beforehand to simplify the computation.

5.4 Change Detection Mechanism

When the busy channel probability is increased from β^*_1 to some higher detectable value, say β_2 , there are new nodes joining the network. Any existing nodes i can then use (4-5) to determine $\tau_i = 1 - \prod_{j \neq i}(1 - \alpha_j)$. With (4-6) and the approximation in (4-8), we have:

$$\tau_i = \sum_{k=0}^m \beta_2^k (\Delta^*_1 \sum_{j=1}^{N-1} (1/t_j) + \sum_{l \in \text{change}} (1/t_l)) \quad (5-9)$$

where node $j \in (1, 2, \dots, N - 1)$ the existing node and node $l \in \text{change}$ the new nodes. As node i knows the values of β_2 , τ_i , $\sum_{j=1}^{N-1}(1/t_j)$ and Δ^*_1 , it can use (5-9) to determine $\sum_{l \in \text{change}}(1/t_l)$ and then use (5-5) and (5-8) to find the new optimal operating point. As for new node l , a similar procedure can be performed to find the sum $\sum_{j=1}^{N-1}(1/t_j)$ but they first need to sense the β^*_1 for a short period before starting to transmit packets.

When the busy channel probability is decreased from β^*_1 to some lower value, say β_3 , there are nodes leaving the network (i.e., nodes become inactive), τ_i can be determined as:

$$\tau_i = \sum_{k=0}^m \beta_3^k (\Delta^*_1 \sum_{l \in \text{current}} (1/t_l)) \quad (5-10)$$

where $l \in \text{current}$ are the nodes still staying in the network. Using (5-10), node i can readily determine $\sum_{l \in \text{current}} (1/t_l)$ and find the new operating point. The complete process of traffic estimation and throughput adjustment is summarized in Table 5-1.

Table 5-1: Pseudo-code of the proposed adjustment algorithm

```

c = 0;
for k = 1; k < I; k++
    while (c + + < cMAX)
        Perform data transmission and record  $\beta_k$ 
    end
    if (k == 1)
         $\sum_{j \neq i} (1/t_j) = g(\beta_k)$  (using (4-9))
         $\lambda_i = \text{RateUpdate}(\sum_{j \neq i} (1/t_j))$ 
    else if ( $|\beta_k - \beta_{last}| < \beta_{THR}$ )
        // Do not change the transmission rate
    else if ( $\beta_k > \beta_{last}$ )
         $\sum_{j \neq i} (1/\lambda_j) = g(\beta_k)$  (using (4-9))
        Obtain new nodes' traffic:
         $\sum_{l \in \text{change}} (1/t_l) = \sum_{j \neq i} (1/\lambda_j) - \Delta^* \sum_{j \neq i} (1/t_j)$ 
         $\lambda_i = \text{RateUpdate}(\sum_{j \neq i} (1/t_j) + \sum_{l \in \text{change}} (1/t_l))$ 
    else if ( $\beta_k < \beta_{last}$ )
         $\sum_{l \in \text{current}} (1/\lambda_j) = g(\beta_k)$  (using (4-9))
        Obtain the current traffic:
         $\sum_{l \in \text{current}} (1/t_l) = \sum_{l \in \text{current}} (1/\lambda_j) / \Delta^*$ 
         $\lambda_i = \text{RateUpdate}(\sum_{l \in \text{current}} (1/t_l))$ 
    end
    c = 0
end

function  $\lambda_i = \text{RateUpdate}(\text{Traffic})$ 

```

```

 $\beta_{last} = \beta^* = h(\text{Traffic})$ 
 $\Delta^* = \Delta^*(\beta^*, \text{Traffic})$  (using (5-5))
 $\lambda_i = t_i / \Delta^*$ 
end

```

Remark 5.1: In the case that the traffic of existing nodes change, it can be readily dealt with using the proposed algorithm. The change of the traffic will be reflected on the aggregate traffic rates and can be estimated using (5-9) and (5-10).

5.5 Experimental Results

The proposed distributed algorithm has been implemented and extensively tested using the TelosB node [74]. TelosB consists of a Texas Instrument MSP430F1611 microcontroller and an IEEE 802.15.4-complaint CC2420 radio transceiver. The proposed algorithm is built on top of the TinyOS operating system [96], using a dialect of C language called nesC (network embedded system C language) [97]. The codes for the proposed algorithm occupy about 8-kB program memory. For the medium access control (MAC) layer and the interfaces to the radio stack, the IEEE 802.15.4 slotted CSMA implementation [98] is used. The network is organized using star topology where multiple nodes transmit data to a pre-defined receiver. A packet transmission cycle consisting of transmitting the data packet and waiting and receiving the ACK packet is of 100 symbols long, which is translated to five time slots in the channel state model in Section 4.3. The function value $h(\sum_{j \neq i}(1/t_j))$ is discretized for $\sum_{j \neq i}(1/t_j) \in [0, 0.1]$ with an interval of 0.0025 using a “float” type C array as a look-up table.

In the following discussions, the performance of the algorithm is evaluated under a typical laboratory environment, as shown in Figure 5-1 and Figure 5-2. Each node is

placed on top of a 1-m PVC stand. The network to be tested is assumed to be a sparse and low-traffic network. The transmission power is set to 0 dBm. The application considered is an indoor laboratory monitoring and control system, where sensors with heterogeneous traffic transmit packets to a central coordinator (controller). The traffic in such a system is unsaturated, but within a certain time interval, a minimum number of successful packets are expected (as “throughput demand”) for each sensor node in order to stabilize a control system, as discussed in [91, 99], or to enable real-time monitoring. To take into account the effect of multi-path fading, the sensor nodes and the central coordinator are randomly placed in the nine spots in Figure 5-2 and are shuffled after each experiment.

Figure 5-1 The Testing Area

Figure 5-2 the Floor Plan of the Testing Area

The homogeneous case where each sensor node in the network has the same throughput demand is first tested. Different numbers of sensor nodes in the network are evaluated, ranging from three to seven. Each node is assigned a throughput demand of $1/200$. Each experiment is run for 300 s and repeated 3 times and more than 5000 packets are transmitted by each node for each experiment.

The result is shown in Figure 5-3. Figure 5-3 first compares the actual throughput (mean and standard deviation) *versus* the throughput demand. It is observed that the actual throughput is very close to the demand, with an average relative error of 0.43%. The transmission rate (mean and standard deviation) is also compared with the one predicted using the Markov chain model [32]. The result is in general very close but the proposed distributed algorithm performs slightly better in providing the optimal transmission rate based on the actual throughput.

Figure 5-3 Experiment results of homogeneous networks (TR: transmission rate)

Figure 5-4 presents the result for a heterogeneous network consisting of six sensor nodes which are assigned a throughput demand of 1/100, 1/120, 1/140, 1/160, 1/180, 1/200, respectively. The experiment is run for 300 s and repeated 10 times. The actual throughput for each node matches very well with the demands, with an average percentage error of 0.524%.

Figure 5-4 Experiment results of heterogeneous networks (TR: transmission rate)

Table 5-2 compares the proposed method with the Markov chain-based methods. It is shown that the proposed one is able to satisfy the throughput demand with a smaller error than the one achieved by the Markov chain model in both homogeneous networks and heterogeneous networks. This may be because the Markov chain model relies on certain assumptions (e.g., busy channel probability does not depend on backoff stages), which is prone to slight estimation errors. On the other hand, while the proposed algorithm also makes use of such models, the real-time CCA feedbacks can help to correct the modeling error and lead to a more accurate operating point with respect to the throughput demand. Moreover, due to its distributed nature, the proposed algorithm is easier to implement and requires local channel sensing information only while the Markov chain method is more computationally expensive and requires network-wide information. Lastly, the proposed method employs a real-time traffic estimation

method and is able to adapt to possible traffic changes while in the case of the Markov chain method, a new model will need to be solved when there is a traffic change.

Table 5-2 Comparisons of the proposed method and the Markov-chain based Methods.

Method	Proposed Method	Markov Chain-Based Methods
Errors	Homogeneous	0.43%
	Heterogeneous	0.524%
Complexity	easy to implement; able to be stored in a look-up table	computationally intensive; requires solving of multi- dimension Markov chain
Required Information	local information only, e.g., channel sensing result	needs network-wide information, e.g., the number of active nodes
Flexibility	able to adapt traffic changes	requires the traffic to be constant

Figure 5-5 and Figure 5-6 show the experimental results for a network with changes on the number of nodes. Initially Node 1, Node 2 and Node 3 are in the network with throughput demands of 1/100, 1/150, 1/200, respectively. At the second update, Node 4 is injected with a throughput demand of 1/100, followed by injection of Node 5 with a throughput demand of 1/200 at the 4th update. Node 4 and Node 5 become inactive at the 6th update. The update time is set to be 120 s and the threshold β_{THR} is set to 0.02.

Figure 5-5 Busy channel probability in a heterogeneous network with changes on the number of nodes.

Figure 5-6 Actual throughput in a heterogeneous network with changes on the number

Figure 5-5 shows the results of busy channel probability (BCP). The BCPs of Node 1 – 3 changes significantly when Node 4 is injected, with an increment of 0.06, 0.05, 0.02, respectively. According to Section 4, the change of BCP due to the injection of Node 4 is 0.0598 and the maximal fluctuations of the BCPs of the three without any traffic changes are 0.0234, 0.0287 and 0.0331, respectively. Node 3 with the lowest transmission rate suffers most from the noisy measurement of BCP. Nevertheless, as 0.0598 is greater than the maximal fluctuations and all nodes are able to detect the injection of Node 4. However, the detection of Node 5 is difficult as it brings a lower traffic. The BCPs do not change significantly. When Node 4 and Node 5 become inactive, the BCPs of the remaining nodes change significantly, with decrement of 0.02, 0.04 and 0.06.

Despite the fluctuations on BCP, each node is able to adjust the transmission rate to meet the throughput demand. The actual throughput is plotted in Figure 5-6. It is observed that the average throughput of each node is very close to the demand, with an average percentage error of 0.875% at the optimal point.

5.6 Summary

This chapter presents a fully distributed rate adjustment algorithm for heterogeneous CSMA networks with time-varying traffic. The algorithm enables each node in the CSMA network to tune its transmission rate to a desired level with respect to a given throughput demand without any central coordination.

The novelty of the proposed algorithm lies in the following two aspects. First, with the traffic estimation method presented in Chapter 4, each node is able to estimate the packet success rate at equilibrium point and adjust the transmission rate to meet the throughput

demand. Compared with existing methods that typically has a prediction error of several percent, the proposed algorithm only yields an average error of 0.43% for homogeneous networks and 0.524% for heterogeneous networks and does not require either complex modeling or central coordination. Second, the algorithm is more flexible in that it is robust against time-varying traffic and can adjust to a new transmission rate should there be any traffic changes.

The proposed algorithm can be used for both homogeneous and heterogeneous CSMA networks. Particularly, it is most suitable for applications with certain throughput requirements. For example, in an intra-vehicular or intra-satellite control system, it is often required that every sensor sends a minimum number of measurement packets to the controller to guarantee certain control performance. In this case, the algorithm can be employed to determine the actual transmission rate required. As for practical considerations, the proposed method simply makes use of CCA information and does not require modifications on the CSMA protocol. It is thus easy to implement and computationally inexpensive with the use of a look-up table. Our implementation based on the TinyOS [96, 98] platform also shows its compatibility with prevailing protocol stack.

The method proposed in Chapter 4 and Chapter 5 can be affected by fluctuation of traffic estimation that naturally occurs in a random access network. Analysis has been conducted in Section 4.4.2 to evaluate its effect on the network performance. The proposed study suggests that the fluctuation has only a minor effect on the traffic estimation and can be further mitigated by increasing the update interval. The proposed method also assumes a moderate traffic pattern. It mainly targets at control system and monitoring applications (rather than heavy-loaded networks such as file uploading

services). For such applications, it is shown in Section 4.4.2 that it has negligible effect on the network performance.

In this chapter, the rate adjustment algorithm assumes that the throughput demand is always feasible. However, how to examine whether a throughput profile is feasible remains unclear. In the next chapter, the maximum throughput of a CSMA network is investigated. The distributed rate adjustment using clear channel assessment for throughput maximization will be explored.

6. A Probabilistic Backoff Protocol for Throughput

Maximization in a CSMA Network

6.1 Introduction

In Chapters 4 and 5, the traffic estimation and throughput adjustment of the IEEE 802.15.4 CSMA network have been presented. In Chapter 5, a rate adjustment algorithm for throughput tuning in a CSMA network has been developed. It is based on the assumption that each node has unsaturated traffic. When extending it to a saturated traffic condition, one important problem is how to determine and achieve the maximum throughput. As mentioned in Chapter 2, analysis has been performed to investigate the throughput limit of an IEEE 802.15.4 CSMA network [53] and it has been discovered that the binary exponent backoff used in IEEE 802.15.4 is inefficient in terms of throughput performance [51]. Moreover, Both Chapter 4 and Chapter 5 have assumed that the process of carrier sensing is error-free. While this assumption is valid in many applications, it is unrealistic under several scenarios. For example, when a threshold-based energy detector is used, if the received power does not dominate the additive noise, the carrier sensing is subject to random errors [18]. These errors may result in misguided transmission efforts and significantly affect the throughput performance.

This chapter aims to thoroughly examine the above issues. Specifically, the throughput inefficiency of an IEEE 802.15.4 CSMA network is examined and a novel energy-efficient backoff protocol that can sustain the maximum throughput is proposed. The proposed protocol enables distributed traffic estimation and throughput optimization under imperfect carrier sensing condition.

6.2 Preliminaries

A single-hop CSMA network where N nodes transmit data packets to their corresponding receivers is considered. It is assumed that access to the wireless medium is time slotted. Each data packet takes up L time slots. Assume that each node is in saturated state and thus always has packets buffered.

The interference in the network is characterized by the complete conflict relationship: if more than one of the N nodes start transmitting at the same time, the transmissions fail.

Carrier sensing is performed at the start of each slot. The sensing lasts for a fraction of a time slot. A threshold of the energy in the wireless medium is imposed to determine whether the channel is idle or busy. When the channel is idle, the node proceeds to transmit a data packet in the next slot. Otherwise, it backs off for a random number of slots before the next carrier sensing. The details of the backoff algorithm will be discussed in the next section.

Due to the noisiness and errors of the wireless medium, the threshold-based energy detection inevitably results in sensing errors. The probability of false alarm p_f represents the probability that the channel is idle but the node considers it busy. The probability of miss detection p_m represents the probability that the channel is busy but the node senses an idle result [100].

6.3 Probabilistic Backoff CSMA

6.3.1 Operations

The details of the proposed algorithm named probabilistic backoff CSMA (PB-CSMA) are shown in Algorithm 6-1. Each node starts by entering the probabilistic backoff process. It will then jump among the states of probabilistic backoff, extra backoff, packet transmission and carrier sensing, according to the conditions specified in Algorithm 6-1. The function UNIFORM returns a uniformly distributed number between $[0, 1]$. The variable m denotes the maximal length of the probabilistic backoff phase and the p_i is the transmission threshold for each backoff slot i . Apparently, the different selections of p_i and m result in different backoff strategies and thus different carrier sensing probabilities.

Table 6-1: PB-CSMA

PROBABISTIC BACKOFF:

$i = 0$
while $i < m$:
 $x_i = \text{UNIFORM}(0, 1)$
 IF $x_i < p_i$
 goto **CARRIER SENSING**
 ELSE $i++$
goto **CARRIER SENSING**

CARRIER SENSING:

IF busy:
 goto **EXTRA BACKOFF**
ELSE:
 goto **TRANSMIT**

TRANSMIT:

transmit data packet to the receiver
goto **PROBABILISTIC BACKOFF**

EXTRA BACKOFF:

perform backoff for $\lfloor L/2 \rfloor$ slots
goto **PROBABILISTIC BACKOFF**

6.3.2 Markov Chain Modeling

Figure 6-1 Markov Chain Model of PB-CSMA

The behavior of every participating node using the PB-CSMA protocol can be described using a 2-D Markov chain as in Figure 6-1. Denote $(s(t), c(t))$ as the two states of the Markov chain. $s(t) = 0, 1, 2$ means the tagged node is in the backoff state, carrier sensing state and packet transmission state, respectively. $c(t)$ describes the backoff counter and $c(t) = -1$ means that the node is either in carrier sensing or packet transmission. The states from $(0, x_1)$ to $(0, x_m)$ are called the probabilistic backoff phase. A node trying to initialize a new packet transmission will first go to state $(0, x_1)$. It will then perform a carrier sensing, i.e., going to $(1, -1)$ with probability p_1 . Otherwise it will continue the probabilistic backoff phase by going to $(0, x_2)$. For every x_k , $0 < k < m$, the probability of going to carrier sensing is p_k . At most there are m backoff slots, after which the node will always perform a carrier sensing. The symbol β' denotes the sensed busy channel probability. Note that due to imperfect carrier sensing, β' is generally not the same as the actual busy channel

probability β . Should the result of carrier sensing be idle, the node will proceed to transmitting a packet, i.e., going to state $(2, -1)$. When the transmission is completed, the node will go back to $(0, x_1)$ and start a new transmission cycle. If the node senses a busy channel, it will first backoff $\lfloor L/2 \rfloor$ slots. This period is called the extra backoff phase. After that, the node proceeds to state $(0, x_1)$. The reason for the node to back off additional $\lfloor L/2 \rfloor$ slots is to wait until the on-going transmission is completed and to avoid unnecessary channel sensing.

The state transitions associated with the discrete-time Markov chain are

$$P(2, -1 | 1, -1) = 1 - \beta' \quad (6-1)$$

$$P(0, x_1 | 2, -1) = \frac{1}{L} \quad (6-2)$$

$$P(0, i + 1 | 0, i) = 1, 0 \leq i \leq \lfloor L/2 \rfloor - 1 \quad (6-3)$$

$$P(0, x_1 | 0, \lfloor L/2 \rfloor) = 1 \quad (6-4)$$

$$P(0, x_{i+1} | 0, x_i) = 1 - p_i, 1 \leq i \leq m - 1 \quad (6-5)$$

$$P(1, -1 | 0, x_m) = 1 \quad (6-6)$$

Equation (6-1) is the transition from carrier sensing to transmitting a packet, which occurs if the channel is not busy. Equation (6-2) describes the probability of finishing the on-going packet transmission and going to the state $(0, x_1)$ from packet transmission, which depends on the packet length L . Equations (6-3) and (6-4) represent the increment of the backoff counter in the extra backoff phase, which occurs with probability 1. Equation (6-5) gives the probability of continuing in the backoff phase in the probabilistic backoff phase. Equation (6-6) shows the transition from the last backoff state in the probabilistic backoff phase to carrier sensing state.

With the state transitions, the stationary probability can be derived as follows

$$P_{2,-1} = (1 - \beta')P_{1,-1} \quad (6-7)$$

$$P_{1,-1} = \sum_{i=1}^{m-1} p_i P_{0,x_i} + P_{0,x_m} \quad (6-8)$$

$$P_{0,i} = \beta' P_{1,-1}, 0 \leq i \leq \lfloor L/2 \rfloor \quad (6-9)$$

$$P_{0,x_1} = P_{0,\lfloor L/2 \rfloor} = \beta' P_{1,-1} + \frac{1}{L} P_{2,-1} \quad (6-10)$$

$$P_{0,x_i} = (1 - p_i)P_{0,x_{i-1}}, 2 \leq i \leq m \quad (6-11)$$

Using the normalization condition, from (6-7) to (6-11), $P_{1,-1}$ can be obtained as follows

$$P_{1,-1} = \frac{1}{2 + \lfloor L/2 \rfloor \beta' + (\sum_{i=2}^m \prod_{j=1}^{i-1} (1 - p_j) + 1) \frac{\beta' L + 1 - \beta'}{L}} \quad (6-12)$$

$P_{1,-1}$ is the probability that a node senses the channel in a random slot. It indicates how frequently a node attempts to utilize the channel resource.

6.4 Non-Persistent CSMA with Imperfect Sensing

In this section, the throughput of a non-persistent CSMA is discussed. The throughput is derived as a function of carrier sensing probability $P_{1,-1}$, number of active nodes N , packet length L and carrier sensing errors p_m and p_f . For brevity, let $x = P_{1,-1}$. Assume the homogeneity of the network, the channel is sensed busy when at least one packet transmission is on-going. In the presence of sensing errors, the actual busy channel probability β of one particular node can be adapted from [51] and [32] as

$$\beta = L(1 - (1 - x)^{N-1}) \left((1 - \beta)(1 - p_f) + \beta p_m \right) \quad (6-13)$$

In (6-13), $1 - (1 - x)^{N-1}$ denotes the probability that at least one of the nodes performs the carrier sensing and such nodes send a packet with a length of L if the

channel is sensed idle, i.e., $(1 - \beta)(1 - p_f) + \beta p_m$. With (6-13), β can be explicitly derived as

$$\beta = \frac{(1 - p_f)L(1 - (1 - x)^{N-1})}{1 + (1 - p_f - p_m)L(1 - (1 - x)^{N-1})} \quad (6-14)$$

A node can transmit a successful packet if it senses an idle slot while none of other nodes perform carrier sensing at that slot. This probability can be characterized as $(1 - x)^{N-1} (1 - \beta)(1 - p_f)$. Multiplying it by x and L yield the normalized throughput of a single node. The system throughput $T(x)$ is the sum of the throughput of all the nodes in the network. $T(x)$ can thus be expressed as

$$T(x) = x(1 - x)^{N-1}(1 - \beta)(1 - p_f)LN \quad (6-15)$$

Substituting (6-14) into (6-15) yields

$$T(x) = \frac{x(1 - x)^{N-1}(1 - p_mL(1 - (1 - x)^{N-1}))}{1 + (1 - p_f - p_m)L(1 - (1 - x)^{N-1})}(1 - p_f)LN \quad (6-16)$$

The objective is to find the optimal carrier sensing probability x^* that maximizes the throughput $T(x)$. Differentiating $T(x)$ with respect to x gives

$$\frac{dT}{dx} = \frac{(((1-xN)(1-a\tau)-a(N-1)x(1-\tau))(b\tau+1)-b(N-1)x(1-\tau)(1-a\tau))(1-x)^{N-2}}{(b\tau+1)^2} \quad (6-17)$$

where $a = p_mL$, $b = (1 - p_m - p_f)L$ and $\tau = (1 - (1 - x)^{N-1})$. It can be seen that

$\lim_{x \rightarrow 0} \frac{d(T/(1-x)^{N-2})}{dx} > 0$ and $\lim_{x \rightarrow 1} \frac{d(T/(1-x)^{N-2})}{dx} < 0$. As $\frac{dT}{dx}$ is continuous when $x \in (0, 1)$,

according to intermediate value theorem, there exists at least one $x \in (0, 1)$ such that

$\frac{dT}{dx} = 0$. Furthermore, we have the following theorem.

Theorem 6-1:

(1) A solution of $\frac{dT}{dx} = 0$ for $x \in (0, 1)$ satisfies the following equation

$$x = g(x) = \frac{1 + (b - a)\tau - ab\tau^2}{-abN\tau^2 + (a + b - 2aN)\tau + (N + (a + b)(N - 1))} \quad (6-18)$$

where $a = p_m L$, $b = (1 - p_m - p_f)L$ and $\tau = (1 - (1 - x)^{N-1})$.

(2) $g(0) = 1/(N + (1 - p_f)L(N - 1)) > 0$ and $g(1) = \frac{1}{N} < 1$. Furthermore,

the derivative of $g(x)$, $g'(x)$, is always smaller than 1 when $x \in (0, 1)$.

(3) Equation (6-18) has a unique solution x^* and so $T(x)$ has the maximum value at $x = x^*$.

Proof:

(1) $g(x)$ can be readily obtained by rearranging $\frac{dT}{dx}$.

(2) Following (1), $g(0)$ and $g(1)$ can be readily obtained. To investigate the derivative of $g(x)$, we first rewrite $g(x)$ in the following form for ease of expression

$$g(x) = \frac{A\tau^2 + B\tau + 1}{C\tau^2 + D\tau + E}$$

where $A = -ab$, $B = b - a$, $C = -abN$, $D = -2aN + a + b$ and $E = N + (a + b)(N + 1)$. $g'(x)$ can be determined as

$$g'(x) = \frac{(AD - BC)\tau^2 + (2AE - 2C)\tau + (BE - D)}{C^2\tau^4 + 2CD\tau^3 + (D^2 + 2CE)\tau^2 + 2DE\tau + E^2}$$

Substituting $A = -ab$, $B = b - a$, $C = -abN$, $D = -2aN + a + b$ and $E = N + (a + b)(N + 1)$ into $g'(x)$ yields

$$g'(x) = \frac{(N - 1)(b + a + b^2 - a^2 - a^2b - ab^2)}{N^2 + 2(a + b)(N - 1)N + (a + b)^2(N - 1)^2}$$

$$= \frac{(N-1)(b+a+(1-a)b^2-(b+1)a^2)}{N^2+(N-1)(2aN+2bN+(N-1)(a+b)^2)} < 1$$

(3) For $x = g(x)$, the slope of the left hand side is always 1. As $g(0) > 0$, $g(1) < 1$ and $g'(x) < 1$, it guarantees that there exists one intersection, namely the fixed point x^* , between x and $g(x)$. Moreover, as $g'(x) < 1$, $x > g(x)$ always follows when $x > x^*$. Thus, the fixed point is unique [47].

It immediately follows that when $x = x^*$, $\frac{dT}{dx} = 0$. As $\frac{dT}{dx} > 0$ when $x < x^*$ and $\frac{dT}{dx} < 0$ when $x > x^*$, T achieves its maximum when $x = x^*$.

Figure 6-2 Normalized Throughput as a Function of Carrier Sensing Probability

As an example, Figure 6-2 shows the relation between system throughput T versus carrier sensing probability x for networks with different number of nodes as well as different levels of carrier sensing errors. Under different scenarios, it is observed that there always exists a unique point such that the throughput is maximized.

6.5 Distributed Probabilistic Backoff Algorithm

6.5.1 Achievability Analysis

In Section 6.3, the relationship between the carrier sensing probability and the probabilistic backoff phase is derived. In Section 6.4, the optimal carrier sensing probability under imperfect sensing conditions is derived. The problem remains whether the optimal carrier sensing probability can be achieved by tuning the probabilistic backoff process.

From Section 6.4, it can be shown that the optimal carrier sensing probability lies between $\left(1/\left(N + (1 - p_f)L(N - 1)\right), 1/N\right)$. In (6-12), as the length of the probabilistic phase m and each probability in that phase can be arbitrarily tuned, the probabilistic backoff process $\sum_{i=1}^m \prod_{j=1}^{i-1} (1 - p_j)$ can be practically set to any values in $(0, +\infty)$. When it goes to infinity, the actual carrier sensing probability can be as low as 0 and the lower bound of the optimal carrier sensing probability $1/\left(N + (1 - p_f)L(N - 1)\right)$ can always be fulfilled.

When $\sum_{i=1}^m \prod_{j=1}^{i-1} (1 - p_j)$ is 0, i.e., there is no probabilistic backoff phase, $P_{1,-1}$ can be determined according to (6-12) as

$$\begin{aligned} P_{1,-1} &= \frac{1}{2 + \lfloor L/2 \rfloor \beta'} \\ &\geq \frac{1}{2 + \lfloor L/2 \rfloor} \end{aligned} \tag{6-19}$$

As $P_{1,-1}$ is a decreasing function of $\sum_{i=1}^m \prod_{j=1}^{i-1} (1 - p_j)$ and the latter one can be arbitrarily tuned, thus in practice, $P_{1,-1}$ can take any value in $[0, 1/(\lfloor L/2 \rfloor + 2)]$. Since

it is almost always the case that $\left(1/\left(N + (1 - p_f)L(N - 1)\right), 1/N\right) \in [0, 1/(\lfloor L/2 \rfloor + 2)]$, any optimal carrier sensing probability can be achieved.

6.5.2 Distributed Estimation and Tuning

In Section 6.4, the optimal carrier sensing probability is derived given that the number of active nodes in the network is known a priori. This assumption is restrictive in distributed networks. In this section, an algorithm for estimating the number of active nodes using busy channel probability is presented. Once the number of active nodes is known, the optimal carrier sensing probability can be obtained by the aforementioned fixed point iteration.

Suppose that each node updates its estimate on the number of active nodes periodically. The proposed distributed algorithm first collects the carrier sensing results in the current update interval and uses them to determine the sensed busy channel probability β' . Then β and β' can be related as $\beta' = (1 - p_m)\beta + p_f(1 - \beta)$ and thus β can be derived as $(\beta' - p_f)/(1 - p_m - p_f)$. From (6-14), once β and x are known, the number of active nodes can be estimated and this relationship can be expressed as $N_n = h(\beta, x)$, where N_n is an estimate of N at the n -th update interval and the function $h(\beta, x)$, can be numerically determined from (6-14). It is intuitive that $h(\beta, x)$ is an increasing function of β .

Let x^* be the optimal carrier sensing probability that satisfies (6-18) for a given N_n . Once N_n is known, x^* can be determined based on Theorem 1. Then each node tunes the length and the probabilities of the probabilistic backoff phase such that $x = x^*$. The most straightforward way to construct the backoff phase is to set $p_j = 1/m, 1 \leq j \leq m - 1$. In this case, the term $\sum_{i=1}^m \prod_{j=1}^{i-1} (1 - p_j)$ in (6-12) can be expressed as

$$\sum_{i=1}^m \prod_{j=1}^{i-1} (1 - p_j) = \sum_{i=1}^m (1 - 1/m)^{i-1} = m(1 - (1 - 1/m)^m) \quad (6-20)$$

Substituting (6-20) into (6-12), the optimal m such that $x = x^*$ can be readily found.

In summary, the distributed algorithm simply operates as follows:

- (1) *Calculation of β* : At the end of each update interval, calculate the actual busy channel probability β from the sensed busy channel probability β' ;
- (2) *Calculation of N_n* : Calculate the estimated number of active nodes using $h(\beta, x)$;
- (3) *Calculation of x^** : Based on the estimated N_n , calculate the optimal carrier sensing probability by applying the fixed point iteration;
- (4) *Construction of the probabilistic backoff phase*: Based on the obtained x^* , calculate the optimal length of the probabilistic backoff phase m such that $x = x^*$.

Remark 6.1: The most straightforward way to implement the probabilistic backoff is to use a random number generator that produces a uniformly distributed number r_i between $[0, 1]$ for every slot x_i and compares the random number with the corresponding probability $1/m$. If $r_i < 1/m$, the node jumps to carrier sensing state. Otherwise it goes into the next backoff slot. However, this approach requires the node to stay awake at each slot, which can be energy consuming. Preferably, before entering the probabilistic backoff phase, a node can generate an ordered array of random numbers and record the first entry, say r_c , that is smaller than $1/m$. The node can then turn to sleep mode at the start of the probabilistic backoff phase and only wakes up at slot x_c .

6.5.3 Sensitivity Analysis

The distributed algorithm relies on obtaining β' from the carrier sensing results. However, carrier sensing results are inherently random and consequently, the β'_t obtained at each update interval t is a random variable and may deviate from its nominal value β' . In this section, this deviation is first characterized as a function of the length of the update interval I . The effect of deviation on the tuning of carrier sensing probability is derived. A relationship between the throughput performance and the deviation of β' is established, giving guideline on how to choose an appropriate update interval with respect to a given convergence level of the throughput.

Every carrier sensing can be considered independently and identically distributed (*i.i.d.*) with probability β' . In other words, each sensing is a Bernoulli trial. The number of busy carrier sensing results out of c sensing results follow a binomial distribution $B(c, \beta')$ with a variance of $\beta'(1 - \beta')$. Consequently, for an interval t with c carrier sensing results, the obtained β'_t is approximately normally distributed with a variance of $\beta'(1 - \beta')/c^2$. It is more convenient to use the update interval I (in slots) instead of c . They can be related using $I = c/x$ and the relationship between the standard deviation of β' and I can be written as

$$s = \text{Std}(\beta'_t) = \frac{\sqrt{\beta'(1 - \beta')}}{Ix} \quad (6-21)$$

Denote $\Delta\beta'$ as the deviation of β'_t from its nominal value β' . Using a $\alpha\%$ confidence level, the minimum and maximum of $\Delta\beta'$ are $-\epsilon s$ and ϵs respectively, where ϵ is the z-value corresponding to $\alpha\%$.

Next the effect of $\Delta\beta'$ on the deviation of the carrier sensing probability Δx from the optimal point x^* is investigated. Assuming that N , L , p_m and p_f remain unchanged, according to the chain rule of partial differentiation, the relationship can be outlined as

$$\Delta x = \frac{\partial x^*}{\partial \beta'} \Delta\beta' = \frac{\partial x^*}{\partial N} \frac{\partial N}{\partial \beta} \frac{\partial \beta}{\partial \beta'} \Delta\beta' \quad (6-22)$$

When $x = x^*$, $\frac{\partial N}{\partial \beta}$ can be derived from (6-14) as

$$\frac{\partial N}{\partial \beta} = \frac{-(1 - p_f)}{\ln(1 - x^*)(L(1 - \beta') - \beta)(1 - \beta')} \quad (6-23)$$

While $\frac{\partial \beta}{\partial \beta'}$ can be easily related as $1/(1 - p_m - p_f)$, $\frac{\partial x^*}{\partial N}$ cannot be explicitly found.

However, it can be numerically determined: Once x^* is found using fixed point iteration, the difference between the two adjacent x^* values can be used to approximate

$$\frac{\partial x^*}{\partial N}.$$

Combining (6-21) and (6-22), Δx can be bounded with an $\alpha\%$ confidence level as

$$|\Delta x| \leq \frac{\partial x^*}{\partial N} \frac{-\epsilon(1 - p_f) \sqrt{\frac{\beta'}{(1 - \beta')}}}{L x^* \ln(1 - x^*)(1 - p_m - p_f)(L(1 - \beta') - \beta)} \quad (6-24)$$

To further investigate the effect of Δx on the throughput performance, we modify (6-15) considering that each node's carrier sensing probability may slightly deviate from the optimal value. For an arbitrary node i , its throughput can be adapted from (6-15) as follows:

$$T_i(x) = x_i \prod_{j \neq i} (1 - x_j) (1 - \beta) (1 - p_f) L \quad (6-25)$$

As each x_j is close to the optimal value x^* , $\prod_{j \neq i} (1 - x_j)$ can be approximated as $(1 - x^*)^{N-1}$. As a result, T_i depends on x_i and β . The deviation of the throughput of node i , ΔT_i can be bounded as follows:

$$\begin{aligned} |\Delta T_i| &= \left(\frac{\partial T}{\partial x} \frac{\partial x}{\partial \beta'} + \frac{\partial T}{\partial \beta} \frac{\partial \beta}{\partial \beta'} \right) \Delta \beta' \\ &\leq \left(x^* + \frac{\partial x^*}{\partial N} \frac{(1-p_f)(1-\beta)}{\ln(1-x^*)(L(1-\beta')-\beta)} \right) \frac{\epsilon(1-x^*)^{N-1}(1-p_f)L\sqrt{\beta'(1-\beta')}}{Ix^*(1-p_m-p_f)} \end{aligned} \quad (6-26)$$

Given a requirement on $|\Delta T_i|$, one can readily compute I .

Remark 6.2: If I is too long, nodes may not be able to adapt to traffic changes promptly. An effective way to reduce I without causing too much deviation on the throughput is to use a smoothing filter when estimating the number of active nodes as follows [13, 47]

$$N_n = \lceil \alpha N_n + (1 - \alpha) N_{n-1} \rceil \quad (6-27)$$

where $\alpha \in (0, 1)$. Smaller α will reduce the deviation better, at the cost of slowing the convergence process.

6.6 Numerical Results

In this section, the throughput performance of the proposed algorithm is investigated, using both simulation and analysis. A WPAN network consisting of N transmitters and one sink receiver is considered. The transmitters are subject to carrier sensing errors during the clear channel assessment due to channel error or noise. The packet length is defined in terms of time slots. The analytical throughput of the proposed algorithm is obtained using (6-16). Then the fixed point iteration is used to find the maximum. For IEEE 802.15.4 CSMA, the result is obtained from [51]. The other enhanced methods of the IEEE 802.15.4 are obtained from [51, 84, 101]. The simulation is performed based on the PB-CSMA protocol described in Section 6.3.

6.6.1 Throughput Performance

Figure 6-3 Throughput Comparison

Figure 6-3 shows the analytical throughput comparison of the proposed PB-CSMA with IEEE 802.15.4 CSMA [51] as well as other enhanced methods [51, 84, 101] under perfect carrier sensing condition. The packet length L of both protocols is set to 8. The “original” obtained from [51] refers to the default IEEE 802.15.4 CSMA without ACK and without retransmission, where the MAC layer parameters are set to the default values i.e., minimum binary exponent $minBE$ is set to 3 and the maximal binary exponent $maxBE$ is set to 5 and the backoff limit $maxBO$ is set to 4). It is shown that the throughput drops significantly when the number of active nodes increases. As a summary, the “BE limit” gives the highest throughput that can be achieved using the IEEE 802.15.4 CSMA [51] with the optimum parameter settings (i.e., $minBE$, $maxBE$ and $maxBO$). However, it is very difficult to tune the parameters to the optimum in a distributed manner. The “Ling et al” is a modified version of the original IEEE

802.15.4 CSMA proposed in [51], which simply relaxes the upper limit on the binary exponent. It thus results in longer backoff period and lower the network traffic especially when there are a lot of active nodes. The “ABE” [101] is able to sustain a higher throughput when the number of nodes is less than 60 and it drops gradually thereafter. However, the ABE is a centralized method which requires the receiver to stay awake to calculate the probability of idle slots. The Fibonacci backoff algorithm [84] performs the backoff based on the Fibonacci sequence, where the sequence length is set to 10. It is able to achieve higher throughput than the “Ling et al” method but less than the “BE limit”.

Figure 6-4 Analytical Throughput of PB-CSMA with Different Levels of Carrier Sensing Errors

Figure 6-5 Analytical Throughput of PB-CSMA with Different Packet Lengths

Figure 6-4 and Figure 6-5 show the effect of carrier sensing errors and packet lengths, respectively, on the analytical system throughput. For Figure 6-4, p_m and p_f are both set to 0.05. For Figure 6-5, the packet length is 4 slots. Figure 6-4 shows that longer packet length will result in higher throughput. This can be explained by the fact that collisions occur when two or more nodes start transmitting packets at the same time and when the packet is longer, the chances of starting a packet transmission is lower during a fixed timeframe and thus the probability of packet collisions is also lower. As expected, Figure 6-5 demonstrates that higher carrier sensing errors will degrade the throughput performance. Especially, other things being equal, *miss detection* is more detrimental than *false alarm*. While the *false alarm* results in unnecessary backoff, it also reduces the probability of packet collisions. For nodes with *miss detection*, they will nevertheless transmit packets even when the channel is busy and consequently all the on-going packets will fail.

6.6.2 Distributed Algorithm

Next the performance of the distributed algorithm is simulated. The system parameters are presented in Table 6-2. The results are obtained under the following assumptions: initially all the nodes assume there are 30 active nodes in the network while there are actually 10, 15 and 20 active nodes respectively, which each node tries to estimate. Based on the estimated results, the distributed algorithm tunes the carrier sensing probability to the optimal levels. The update interval is determined according to (6-26) such that the throughput deviation is below 0.01. Each figure contains 30 trajectories to display the outcome of 30 independent simulations.

Table 6-2 Parameter Settings of PB-CSMA

Parameter	Value
Data Rate (kbps)	250
Update Interval (s)	3
Smoothing Factor	0.1
Slot Length (bits)	80
Packet Length (slots)	8
Simulation Time (s)	150
p_m and p_f	0.05

Figure 6-6 Estimated Number of Active Nodes against Update Interval

Figure 6-7 Carrier Sensing Probability against Update Interval

Figure 6-6 shows the trajectories of the estimated number of active nodes. It is observed that starting from the initial value 30, each estimate for N decreases and converges close to the actual value (denoted in dashed line) after the transit period. The estimated N is then used to tune the carrier sensing probability, which is shown in Figure 6-7. It demonstrates that the algorithm is able to tune the carrier sensing probabilities to the optimal levels (denoted in dashed line).

Figure 6-8 Actual Throughput against Analytical Results

Figure 6-8 presents the comparisons between the actual throughput and the analytical results. Each point is obtained by running simulations of 1000000 slots. It can be shown that the differences between the analytical analysis and the simulation results are stabilized at around 0.03. The difference is mainly due to two reasons. First, the Markov chain model assumes that the network is always uniformly distributed. For example, at a random time slot, the chance of sensing a busy channel purely depends on N and if N is constant, β should always be a constant. However, the actual network

operation may slightly deviate from this assumption. For example, some nodes may have more busy sensing results than others. This non-uniformity becomes more severe when there are fewer nodes in the network. Second, as shown in Figure 6-6 and Figure 6-7, the carrier sensing probabilities will only be tuned to the optimum after the transit period. During the transit period, the network throughput is in a sub-optimal state, which also contributes to the difference.

6.7 Summary

The PB-CSMA proposed in this chapter is a new backoff algorithm that allows a saturated non-persistent CSMA network to achieve optimal throughput. It overcomes the throughput inefficiency that is commonly encountered in various backoff algorithms including the binary exponential backoff used in IEEE 802.15.4 MAC. The results show that it can sustain highest throughput among the backoff algorithms and is theoretically maximum. Moreover, it is a fully distributed algorithm requiring no central coordination and can be readily implemented in a distributed network.

7. Conclusion and Future Work

7.1 Conclusions

This thesis is focused on the distributed traffic estimation and throughput optimization in random access networks. The study is mainly motivated by wireless network control systems, in which 1) the number of nodes may change because of the system dynamics; 2) the data arrival rate (sampling rate of each sensor) may also change; 3) each node may move over time. These changes also cause changes in traffic intensity, channel condition. Since the changes are heavily dependent on the control system dynamics and thus highly unpredictable, it is desirable to have a distributed solution to ensure throughput optimization in a fast changing network. Compared with a centralized network, nodes in a distributed network require little or no information exchange/reporting and can decide upon transmission strategy promptly. The distributed nature of the network also helps reduce the computation complexity.

The estimation and optimization are achieved by first exploring the use of various types of local information. The channel state information is exploited in Chapter 3, from which each node is able to derive the optimal transmission strategy with respect to the channel condition. The result of clear channel assessment is exploited in Chapter 4-6. It can be effectively used for determining the traffic intensity in heterogeneous CSMA networks and the number of active nodes in homogeneous networks. The result of acknowledgment packet is used in Chapter 3 and Chapter 4. It determines the combined effect of packet collision and channel fading.

Based on the local information, Chapter 3 develops a novel transmission strategy named adaptive CSI method for an ALOHA network. Unlike the traditional method

that takes a threshold-based strategy, the proposed method adaptively determines the transmission probability based on the readings of the channel state information. Compared with existing methods, it has been proved that the proposed adaptive CSI method is able to achieve up to 9.9% throughput improvement and 12.3% power reduction for a wide variety of systems. Moreover, given different radio specifications (i.e., radio capture ratio) and channel conditions, this thesis propose simple yet effective guidelines to choose the best transmission strategy that guarantees either maximum throughput or minimum energy consumption.

The results of clear channel assessment and acknowledgement packet are used in Chapter 4 and Chapter 5. A channel-state Markov chain is established in Chapter 4 to relate the local information to the traffic states. Based on the readings of local information, two algorithms are proposed to estimate the traffic states of the network with a very low computational complexity. With the traffic information, Chapter 5 develops a rate adjustment algorithm to tune the actual throughput to a desired level in a distributed manner.

Chapter 6 examines the throughput inefficiency of the traditional binary exponent backoff algorithm. With the use of the result of clear channel assessment, a novel backoff protocol named PB-CSMA has been proposed to achieve throughput optimality in a non-persistent CSMA network under imperfect carrier sensing.

In summary, our results show that with the proper use of local information, throughput improvement and energy efficiency can be achieved without any central coordination. The use of distributed channel-state models also enable distributed characterization of on-going traffic. It can thus capture traffic changes in random access networks. The proposed algorithms can be applied for throughput optimization for both saturated

networks (e.g., file transfer applications) and non-saturated networks (e.g., wireless network control systems).

7.2 Future Work

The following sections outline the suggestion for future work.

7.2.1 Estimation of Hybrid Traffic in Heterogeneous CSMA Networks

In Chapters 4 and 5, two different types of heterogeneous traffic patterns have been considered. While these traffic scenarios apply to a wide range of systems such as network control systems and intra-satellite communication systems, many real-world applications have more complex traffic patterns. For example, unsaturated nodes may co-exist with saturated nodes [71]. Future works may be pursued to coordinate the packet transmissions among different nodes and to optimize the system performance in a CSMA network with hybrid traffic.

7.2.2 Comprehensive Use of Local Information

In Chapter 3, it is assumed that CSI can be acquired accurately. In practice, CSI could be noisy due to various reasons. For example, in a time division duplex (TDD) system, channel reciprocity may not be strictly met and the received signal strength is inherently noisy. In the event that imperfect CSI is obtained, it is important to investigate the effect of imperfect CSI on the network performance.

The use of local information in a CSMA network can be further explored. For example, Chapters 4 and 5 consider each clear channel assessment (CCA) result to be a binary value (i.e., busy/idle). In fact, since each CCA may take up at most two slots and there are four possible outcomes, it is possible to obtain more information on the level of

contention by further processing the results. This may also help to propose novel CCA strategies (e.g., the additional carrier sensing method shown in [83]).

The combination of various forms of local information may result in more accurate estimation. For example, the acknowledgement packet (ACK) from the receiver also reflects how busy the network is. Combining the CCA with the ACK may help characterize the network condition more accurately.

Moreover, in Chapter 4 and Chapter 5, it is assumed that there are no hidden terminals. In the presence of hidden terminals, the traffic intensity will be underestimated and the network will operate in a sub-optimal state. This can be detected using the ACK. With packet acknowledgement, each node can properly calculate the actual throughput and compared with the expected one. If the actual throughput is substantially lower than the expected one, it is likely there are hidden terminals. Optimal points in the presence of hidden terminals can also be explored with the use of ACK.

7.2.3 Co-existence of Different Protocols

In this thesis, it is assumed that all the nodes in the network adopt the same communication MAC layer protocols (e.g., ALOHA, IEEE 802.15.4 CSMA). In real-world applications, nodes may share the bandwidth with other nodes adopting different protocols or “selfish” nodes that do not conform to the standard [38, 102]. For example, IEEE 802.15.4 users such as Xbee devices [103] may need to deal with the contention from WiFi users in a typical office setting. Future work may consider the distributed throughput characterization and optimization under such scenarios.

7.2.4 Co-design and Optimization of Wireless Network Control System

This thesis mainly considers the energy and throughput optimization in the MAC layer. To achieve system-wide optimum performance, it might be necessary to consider the parameter settings in other layers (e.g., transmission power level in physical layer). In a wireless network control system (WNCS), several parameters in the application layer, i.e., the control system, will significantly affect system performance. Moreover, parameter settings in different layers may affect each other. For example, the sampling period of a WNCS determine the packet arrival rate and thus the network traffic intensity. Thus, it is best to jointly optimize the parameters of different layers rather than taking a layered approach. In [104], a preliminary study has been performed to adaptively tune the parameters of both the control system and the MAC layer. However, more research work is needed to consider a more general network scenario.

Author's Publications

- S. Xie, K. S. Low, and E. Gunawan, "An adaptive tuning algorithm for IEEE 802.15. 4-based network control system," in *Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2014 IEEE Ninth International Conference on*, 2014, pp. 1-6.
- S. Xie, G. X. Lee, K. S. Low, and E. Gunawan, "Wireless Sensor Network for Satellite Applications: A Survey and Case Study," *Unmanned Systems*, vol. 2, pp. 261-277, 2014.
- S. Xie, K. S. Low, and E. Gunawan. "A Distributed Transmission Rate Adjustment Algorithm in Heterogeneous CSMA/CA Networks." *Sensors*, vol 15.4, pp. 7434-7453, 2015.
- S. Xie, K. S. Low, and E. Gunawan. "Estimating Heterogeneous Traffic in CSMA Networks at Runtime", *Telecommunication and Signal Processing (TSP), 2015 38th International Conference on*, 2015, pp. 226-231.
- S. Xie, K. S. Low, and E. Gunawan. "Distributed Transmission Probability Control in Fading Channel with State Information", *International Journal of Distributed Sensor Network, Vol. 2015, paper 184629*.

References

- [1] J. Cai and D. Goodman, "General packet radio service in GSM," *Communications Magazine, IEEE*, vol. 35, pp. 122-131, 1997.
- [2] A. Brand and H. Aghvami, "Multiple Access in GSM and (E) GPRS," *Multiple Access Protocols For Mobile Communications: GPRS, UMTS and Beyond*, pp. 99-220, 2002.
- [3] H. Wu, C. Zhu, R. J. La, X. Liu, and Y. Zhang, "FASA: Accelerated S-ALOHA using access history for event-driven M2M communications," *Networking, IEEE/ACM Transactions on*, vol. 21, pp. 1904-1917, 2013.
- [4] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey," *Computer Networks*, vol. 52, pp. 2292-2330, Aug 22 2008.
- [5] J. Gao and I. Rubin, "Analysis of random access protocol under bursty traffic," in *Management of Multimedia on the Internet*, ed: Springer, 2001, pp. 71-84.
- [6] M. Mouly, M.-B. Pautet, and T. Foreword By-Haug, *The GSM system for mobile communications*: Telecom Publishing, 1992.
- [7] S. Sen, D. J. Dorsey, R. Guerin, and M. Chiang, "Analysis of Slotted ALOHA with Multipacket Messages in Clustered Surveillance Networks," *2012 IEEE Military Communications Conference (Milcom 2012)*, 2012.
- [8] S.-Y. Lien, T.-H. Liao, C.-Y. Kao, and K.-C. Chen, "Cooperative access class barring for machine-to-machine communications," *Wireless Communications, IEEE Transactions on*, vol. 11, pp. 27-32, 2012.
- [9] X. Li, H. Liu, S. Roy, J. Zhang, P. Zhang, and C. Ghosh, "Throughput analysis for a multi-user, multi-channel ALOHA cognitive radio system," *Wireless Communications, IEEE Transactions on*, vol. 11, pp. 3900-3909, 2012.

- [10] K. Cohen, A. Leshem, and E. Zehavi, "Game theoretic aspects of the multi-channel ALOHA protocol in cognitive radio networks," *Selected Areas in Communications, IEEE Journal on*, vol. 31, pp. 2276-2288, 2013.
- [11] E. Yaacoub and A. Abu-Dayya, "Automatic meter reading in the smart grid using contention based random access over the free cellular spectrum," *Computer Networks*, vol. 59, pp. 171-183, 2014.
- [12] I. Demirkol, C. Ersoy, and F. Alagoz, "MAC protocols for wireless sensor networks: a survey," *Communications Magazine, IEEE*, vol. 44, pp. 115-121, 2006.
- [13] F. Cali, M. Conti, and E. Gregori, "IEEE 802.11 protocol: Design and performance evaluation of an adaptive backoff mechanism," *IEEE Journal on Selected Areas in Communications*, vol. 18, pp. 1774-1786, Sep 2000.
- [14] M. Khanafer, M. Guennoun, and H. Mouftah, "A Survey of Beacon-Enabled IEEE 802.15. 4 MAC Protocols in Wireless Sensor Networks," *IEEE Communications Surveys & Tutorials*, 2014.
- [15] T. Datasheet, "Crossbow Inc," ed: ed, 2013.
- [16] N. I. Dopico, C. Gil-Soriano, I. Arrazola, and S. Zazo, "Analysis of IEEE 802.15. 4 throughput in beaconless mode on MicaZ under TinyOS 2," in *Vehicular Technology Conference Fall (VTC 2010-Fall), 2010 IEEE 72nd*, 2010, pp. 1-5.
- [17] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer Networks*, vol. 38, pp. 393-422, 2002.
- [18] T. H. Kim, J. Ni, R. Srikant, and N. H. Vaidya, "On the Achievable Throughput of CSMA under Imperfect Carrier Sensing," *2011 Proceedings IEEE Infocom*, pp. 1674-1682, 2011.

- [19] K. Akkarajitsakul, E. Hossain, D. Niyato, and D. I. Kim, "Game Theoretic Approaches for Multiple Access in Wireless Networks: A Survey," *IEEE Communications Surveys and Tutorials*, vol. 13, pp. 372-395, 2011.
- [20] T. Cui, L. J. Chen, and S. H. Low, "A game-theoretic framework for medium access control," *IEEE Journal on Selected Areas in Communications*, vol. 26, pp. 1116-1127, Sep 2008.
- [21] F. T. Hsu and H. J. Su, "Random Access Game in Fading Channels With Capture: Equilibria and Braess-like Paradoxes," *IEEE Transactions on Signal Processing*, vol. 59, pp. 1158-1169, Mar 2011.
- [22] I. Menache and N. Shimkin, "Rate-based equilibria in collision channels with fading," *IEEE Journal on Selected Areas in Communications*, vol. 26, pp. 1070-1077, Sep 2008.
- [23] D. Braess, A. Nagurney, and T. Wakolbinger, "On a paradox of traffic planning," *Transportation Science*, vol. 39, pp. 446-450, 2005.
- [24] IEEE 802.15.4 standard: Wireless Medium Access Control and Physical Layer Specifications for Low-Rate Wireless Personal Area Networks, IEEE, 2006, <http://www.ieee802.org/15/pub/TG4.html>.
- [25] S. Xie, G. X. Lee, K.-S. Low, and E. Gunawan, "Wireless Sensor Network for Satellite Applications: A Survey and Case Study," *Unmanned Systems*, vol. 2, pp. 261-277, 2014.
- [26] B. Shrestha, E. Hossain, and S. Camorlinga, "IEEE 802.15.4 MAC With GTS Transmission for Heterogeneous Devices With Application to Wheelchair Body-Area Sensor Networks," *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, pp. 767-777, Sep 2011.

- [27] G. Bianchi and I. Tinnirello, "Kalman filter estimation of the number of competing terminals in an IEEE 802.11 network," *IEEE Infocom 2003: The Conference on Computer Communications, Vols 1-3, Proceedings*, pp. 844-852, 2003.
- [28] A. L. Toledo, T. Vercauteren, and X. D. Wang, "Adaptive optimization of IEEE 802.11 DCF based on Bayesian estimation of the number of competing terminals," *IEEE Transactions on Mobile Computing*, vol. 5, pp. 1283-1296, Sep 2006.
- [29] C.-T. Chen, *Analog & digital control system design* vol. 2: Saunders College Publishing, 1995.
- [30] M. Mazo, A. Anta, and P. Tabuada, "An ISS self-triggered implementation of linear controllers," *Automatica*, vol. 46, pp. 1310-1314, Aug 2010.
- [31] P. Tabuada, "Event-triggered real-time scheduling of stabilizing control tasks," *IEEE Transactions on Automatic Control*, vol. 52, pp. 1680-1685, Sep 2007.
- [32] K. Ashrafuzzaman and K. S. Kwak, "On the Performance Analysis of the Contention Access Period of IEEE 802.15.4 MAC," *IEEE Communications Letters*, vol. 15, pp. 986-988, Sep 2011.
- [33] P. Park, P. Di Marco, C. Fischione, and K. H. Johansson, "Modeling and Optimization of the IEEE 802.15.4 Protocol for Reliable and Timely Communications," *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, pp. 550-564, Mar 2013.
- [34] P. Park, S. C. Ergen, C. Fischione, and A. Sangiovanni-Vincentelli, "Duty-Cycle Optimization for IEEE 802.15.4 Wireless Sensor Networks," *ACM Transactions on Sensor Networks*, vol. 10, Nov 2013.

- [35] J. Ward and R. T. Compton, "High-Throughput Slotted Aloha Packet Radio Networks with Adaptive Arrays," *Ieee Transactions on Communications*, vol. 41, pp. 460-470, Mar 1993.
- [36] T. Sato, H. Okada, T. Yamazato, M. Katayama, and A. Ogawa, "Throughput analysis of DS/SSMA unslotted ALOHA system with fixed packet length," *Ieee Journal on Selected Areas in Communications*, vol. 14, pp. 750-756, May 1996.
- [37] F. C. Schoute, "Dynamic Frame Length Aloha," *IEEE Transactions on Communications*, vol. 31, pp. 565-568, 1983.
- [38] Y. Jin, G. Kesidis, and J. W. Jang, "A Channel Aware MAC Protocol in an ALOHA Network with Selfish Users," *IEEE Journal on Selected Areas in Communications*, vol. 30, pp. 128-137, Jan 2012.
- [39] I. Menache and N. Shimkin, "Noncooperative power control and transmission scheduling in wireless collision channels," in *ACM SIGMETRICS Performance Evaluation Review*, 2008, pp. 349-358.
- [40] A. B. MacKenzie and S. B. Wicker, "Selfish users in Aloha: a game-theoretic approach," in *Vehicular Technology Conference, 2001. VTC 2001 Fall. IEEE VTS 54th*, 2001, pp. 1354-1357.
- [41] R. B. Myerson, *Game theory*: Harvard university press, 2013.
- [42] S. Sengupta, M. Chatterjee, and K. A. Kwiat, "A Game Theoretic Framework for Power Control in Wireless Sensor Networks," *IEEE Transactions on Computers*, vol. 59, pp. 231-242, Feb 2010.
- [43] Y. Wang, G. Miao, and X. Wang, "An Energy-Efficient Non-Cooperative Game Approach for Channel-Aware Distributed Medium Access Control," in *Vehicular Technology Conference (VTC Fall), 2014 IEEE 80th*, 2014, pp. 1-6.

- [44] I. Menache and N. Shimkin, "Efficient rate-constrained Nash equilibrium in collision channels with state information," in *INFOCOM 2008. The 27th Conference on Computer Communications. IEEE*, 2008.
- [45] Y.-N. Yeh, K.-C. Chen, and Y.-C. Chen, "Throughput in A Cooperative Network and Channel State Information," *Wireless Personal Communications*, vol. 81, pp. 1481-1510, 2015.
- [46] F.-T. Hsu and H.-J. Su, "Throughput improvement in ALOHA networks with power capture and a cheat-proof access control," in *21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, 2010, pp. 1447-1451.
- [47] Y. H. Bae, B. D. Choi, and A. S. Alfa, "Achieving Maximum Throughput in Random Access Protocols with Multipacket Reception," *IEEE Transactions on Mobile Computing*, vol. 13, pp. 497-511, Mar 2014.
- [48] S.-H. Wang and Y. Hong, "Transmission control with imperfect CSI in channel-aware slotted ALOHA networks," *Wireless Communications, IEEE Transactions on*, vol. 8, pp. 5214-5224, 2009.
- [49] J. Sun and E. Modiano, "Opportunistic power allocation for fading channels with non-cooperative users and random access," in *Broadband Networks, 2005. BroadNets 2005. 2nd International Conference on*, 2005, pp. 366-374.
- [50] G. Bianchi, "Performance analysis,of the IEEE 802.11 distributed coordination function," *IEEE Journal on Selected Areas in Communications*, vol. 18, pp. 535-547, Mar 2000.
- [51] X. H. Ling, Y. Cheng, J. W. Mark, and X. M. Shen, "A renewal theory based analytical model for the contention access period of IEEE 802.15.4 MAC,"

- IEEE Transactions on Wireless Communications*, vol. 7, pp. 2340-2349, Jun 2008.
- [52] R. Nelson, *Probability, stochastic processes, and queueing theory: the mathematics of computer performance modeling*: Springer Science & Business Media, 1995.
 - [53] T.-J. Lee, H. R. Lee, and M. Y. Chung, "MAC throughput limit analysis of slotted CSMA/CA in IEEE 802.15. 4 WPAN," *IEEE Communications Letters*, vol. 10, pp. 561-563, 2006.
 - [54] P. Park, P. Di Marco, P. Soldati, C. Fischione, and K. H. Johansson, "A Generalized Markov Chain Model for Effective Analysis of Slotted IEEE 802.15.4," *2009 IEEE 6th International Conference on Mobile Adhoc and Sensor Systems (MASS 2009)*, pp. 285-294, 2009.
 - [55] P. Park, J. Araújo, and K. H. Johansson, "Wireless networked control system co-design," in *Networking, Sensing and Control (ICNSC), 2011 IEEE International Conference on*, 2011, pp. 486-491.
 - [56] A. Faridi, M. R. Palattella, A. Lozano, M. Dohler, G. Boggia, L. A. Grieco, and P. Camarda, "Comprehensive evaluation of the IEEE 802.15. 4 MAC layer performance with retransmissions," *Vehicular Technology, IEEE Transactions on*, vol. 59, pp. 3917-3932, 2010.
 - [57] B. Bellalta, A. Zocca, C. Cano, A. Checco, J. Barcelo, and A. Vinel, "Throughput Analysis in CSMA/CA Networks Using Continuous Time Markov Networks: A Tutorial," in *Wireless Networking for Moving Objects*, I. Ganchev, M. Curado, and A. Kassler, Eds., ed: Springer International Publishing, 2014, pp. 115-133.

- [58] M. Di Francesco, G. Anastasi, M. Conti, S. K. Das, and V. Neri, "Reliability and Energy-Efficiency in IEEE 802.15.4/ZigBee Sensor Networks: An Adaptive and Cross-Layer Approach," *IEEE Journal on Selected Areas in Communications*, vol. 29, pp. 1508-1524, Sep 2011.
- [59] F. Shu, T. Sakurai, M. Zukerman, and H. L. Vu, "Packet loss analysis of the IEEE 802.15.4 MAC without acknowledgments," *IEEE Communications Letters*, vol. 11, pp. 79-81, Jan 2007.
- [60] P. Park, "Traffic Generation Rate Control of Wireless Sensor and Actuator Networks."
- [61] D. Malone, K. Duffy, and D. Leith, "Modeling the 802.11 distributed coordination function in nonsaturated heterogeneous conditions," *Networking, IEEE/ACM Transactions on*, vol. 15, pp. 159-172, 2007.
- [62] P. Di Marco, P. Park, C. Fischione, and K. H. Johansson, "Analytical modelling of IEEE 802.15. 4 for multi-hop networks with heterogeneous traffic and hidden terminals," in *Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE*, 2010, pp. 1-6.
- [63] K. Kosek-Szott, "A comprehensive analysis of IEEE 802.11 DCF heterogeneous traffic sources," *Ad Hoc Networks*, vol. 16, pp. 165-181, May 2014.
- [64] W. Kim, "Short Clear Channel Assessment in Slotted IEEE 802.15. 4 Networks," *Wireless Personal Communications*, vol. 71, pp. 735-744, 2013.
- [65] P. Park, C. Fischione, and K. H. Johansson, "Modeling and Stability Analysis of Hybrid Multiple Access in the IEEE 802.15.4 Protocol," *ACM Transactions on Sensor Networks*, vol. 9, Mar 2013.

- [66] M. E. Rivero-Angeles, D. Lara-Rodríguez, and F. A. Cruz-Pérez, "Random-access control mechanisms using adaptive traffic load in ALOHA and CSMA strategies for EDGE," *Vehicular Technology, IEEE Transactions on*, vol. 54, pp. 1160-1186, 2005.
- [67] M. Bertocco, G. Gamba, A. Sona, and S. Vitturi, "Performance measurements of CSMA/CA-based wireless sensor networks for industrial applications," in *Instrumentation and Measurement Technology Conference Proceedings, 2007. IMTC 2007. IEEE*, 2007, pp. 1-6.
- [68] L. Angrisani, M. Bertocco, G. Gamba, and A. Sona, "Modeling the performance of CSMA-CA based wireless networks versus interference level," in *Instrumentation and Measurement Technology Conference Proceedings, 2008. IMTC 2008. IEEE*, 2008, pp. 376-381.
- [69] A. Doucet, N. De Freitas, and N. Gordon, *An introduction to sequential Monte Carlo methods*: Springer, 2001.
- [70] D. Simon, *Optimal state estimation: Kalman, H infinity, and nonlinear approaches*: John Wiley & Sons, 2006.
- [71] S. H. Nguyen, H. L. Vu, and L. L. H. Andrew, "Performance Analysis of IEEE 802.11 WLANs With Saturated and Unsaturated Sources," *IEEE Transactions on Vehicular Technology*, vol. 61, pp. 333-345, Jan 2012.
- [72] S. Brienza, D. De Guglielmo, C. Alippi, G. Anastasi, and M. Roveri, "A learning-based algorithm for optimal mac parameters setting in IEEE 802.15. 4 wireless sensor networks," in *Proceedings of the 10th ACM symposium on Performance evaluation of wireless ad hoc, sensor, & ubiquitous networks*, 2013, pp. 73-80.

- [73] H. Lee and H. Kwon, "Improving Estimation of the Nearest Neighbor in Mobile Wireless Sensor Networks," ed: Citeseer, 2009.
- [74] T. Datasheet, "Available Online: <http://www.willow.co.uk>," *TelosB_Datasheet.pdf*/(accessed on 12 January 2010).
- [75] N. Abdeddaim, F. Theoleyre, M. Heusse, and A. Duda, "Adaptive IEEE 802.15.4 MAC for Throughput and Energy Optimization," in *Distributed Computing in Sensor Systems (DCOSS), 2013 IEEE International Conference on*, 2013, pp. 223-230.
- [76] B. M. Khan, F. H. Ali, and E. Stipidis, "Improved backoff algorithm for IEEE 802.15.4 wireless sensor networks," in *Wireless Days (WD), 2010 IFIP*, 2010, pp. 1-5.
- [77] S.-T. Sheu, Y.-Y. Shih, and L.-W. Chen, "An adaptive interleaving access scheme (IAS) for IEEE 802.15.4 WPANs," in *Vehicular Technology Conference, 2005. VTC 2005-Spring. 2005 IEEE 61st*, 2005, pp. 1523-1527.
- [78] Q. Liu and A. Czylik, "A collision-aware backoff mechanism for IEEE 802.15.4 wireless sensor networks," in *Wireless Days (WD), 2013 IFIP*, 2013, pp. 1-3.
- [79] J. Y. Ha, T. H. Kim, H. S. Park, S. Choi, and W. H. Kwon, "An enhanced CSMA-CA algorithm for IEEE 802.15.4 LR-WPANs," *IEEE Communications Letters*, vol. 11, pp. 461-463, May 2007.
- [80] P. Di Marco, P. Park, C. Fischione, and K. H. Johansson, "Analytical modeling of multi-hop IEEE 802.15.4 networks," *Vehicular Technology, IEEE Transactions on*, vol. 61, pp. 3191-3208, 2012.

- [81] J.-Y. Um, J.-S. Ahn, and K.-W. Lee, "Evaluation of the effects of a grouping algorithm on IEEE 802.15. 4 networks with hidden nodes," *Communications and Networks, Journal of*, vol. 16, pp. 81-91, 2014.
- [82] B.-H. Lee and H.-K. Wu, "Study on a delayed backoff algorithm for IEEE 802.15. 4 low-rate wireless personal area networks," *Communications, IET*, vol. 3, pp. 1089-1096, 2009.
- [83] B. H. Lee, R. L. Lai, H. K. Wu, and C. M. Wong, "Study on Additional Carrier Sensing for IEEE 802.15.4 Wireless Sensor Networks," *Sensors*, vol. 10, pp. 6275-6289, Jul 2010.
- [84] M. O. B. Yassien, M. K. Salayma, W. E. Mardini, and Y. M. Khamayseh, "Fibonacci Backoff Algorithm for IEEE 802.15. 4/ZigBee," *Network Protocols and Algorithms*, vol. 4, pp. 62-78, 2012.
- [85] P. Cardieri, "Modeling interference in wireless ad hoc networks," *Communications Surveys & Tutorials, IEEE*, vol. 12, pp. 551-572, 2010.
- [86] J. G. Proakis, "Digital communications, 2001," 4th ed: McGraw-Hill, New York.
- [87] E. Kreyszig, *Advanced engineering mathematics*: John Wiley & Sons, 2007.
- [88] J. A. Gutierrez, E. H. Callaway, and R. L. Barrett, *Low-rate wireless personal area networks: enabling wireless sensors with IEEE 802.15. 4*: IEEE Standards Association, 2004.
- [89] L. Tang, K.-C. Wang, Y. Huang, and F. Gu, "Channel characterization and link quality assessment of ieee 802.15. 4-compliant radio for factory environments," *Industrial Informatics, IEEE Transactions on*, vol. 3, pp. 99-110, 2007.

- [90] U. Tiberi, C. Fischione, K. H. Johansson, and M. D. Di Benedetto, "Energy-efficient sampling of networked control systems over IEEE 802.15.4 wireless networks," *Automatica*, vol. 49, pp. 712-724, Mar 2013.
- [91] J. Baillieul, "Feedback designs in information-based control," *Stochastic Theory and Control, Proceedings*, vol. 280, pp. 35-57, 2002.
- [92] L. A. Montestruque and P. Antsaklis, "Stability of model-based networked control systems with time-varying transmission times," *IEEE Transactions on Automatic Control*, vol. 49, pp. 1562-1572, Sep 2004.
- [93] P. Minero, M. Franceschetti, S. Dey, and G. N. Nair, "Data rate theorem for stabilization over time-varying feedback channels," *IEEE Transactions on Automatic Control*, vol. 54, p. 243, 2009.
- [94] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking," *Signal Processing, IEEE Transactions on*, vol. 50, pp. 174-188, 2002.
- [95] P. Li, T. Zhang, and A. E. Pece, "Visual contour tracking based on particle filters," *Image and Vision Computing*, vol. 21, pp. 111-123, 2003.
- [96] P. Levis, S. Madden, J. Polastre, R. Szewczyk, K. Whitehouse, A. Woo, D. Gay, J. Hill, M. Welsh, and E. Brewer, "TinyOS: An operating system for sensor networks," in *Ambient intelligence*, ed: Springer, 2005, pp. 115-148.
- [97] D. Gay, P. Levis, R. von Behren, M. Welsh, E. Brewer, and D. Culler, "The nesC language: A holistic approach to networked embedded systems," *ACM Sigplan Notices*, vol. 38, pp. 1-11, May 2003.
- [98] J.-H. Hauer, "TKN15. 4: An IEEE 802.15. 4 MAC implementation for TinyOS," 2009.

- [99] N. C. Martins, M. A. Dahleh, and N. Elia, "Feedback stabilization of uncertain systems in the presence of a direct link," *IEEE Transactions on Automatic Control*, vol. 51, pp. 438-447, Mar 2006.
- [100] J. W. Chong, D. K. Sung, and Y. Sung, "Cross-Layer Performance Analysis for CSMA/CA Protocols: Impact of Imperfect Sensing," *IEEE Transactions on Vehicular Technology*, vol. 59, pp. 1100-1108, Mar 2010.
- [101] N. Abdeddaim, F. Theoleyre, M. Heusse, and A. Duda, "Adaptive IEEE 802.15.4 MAC for Throughput and Energy Optimization," *2013 9th IEEE International Conference on Distributed Computing in Sensor Systems (IEEE DCOSS 2013)*, pp. 223-230, 2013.
- [102] M. Cagalj, S. Ganeriwal, I. Aad, and J. P. Hubaux, "On selfish behavior in CSMA/CA networks," *IEEE Infocom 2005: The Conference on Computer Communications, Vols 1-4, Proceedings*, pp. 2513-2524, 2005.
- [103] Y. F. Solahuddin and W. Ismail, "Data Fusion for Reducing Power Consumption in Arduino-Xbee Wireless Sensor Network Platform," *2014 International Conference on Computer and Information Sciences (Iccoins)*, 2014.
- [104] S. Xie, K. S. Low, and E. Gunawan, "An adaptive tuning algorithm for IEEE 802.15. 4-based network control system," in *Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2014 IEEE Ninth International Conference on*, 2014, pp. 1-6.