Learning Based Relay and Antenna Selection in Cooperative Networks

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ABSTRACT

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We investigate a cross-layer relay selection scheme based on Q-learning algorithm. For the study, we consider multi-relay adaptive decode and forward (DF) cooperative-diversity networks over multipath time-varying Rayleigh fading channels. The proposed scheme selects relay subsets that maximizes the link layer transmission efficiency without having knowledge of channel state information (CSI). Results show that the proposed scheme outperforms the capacity based cooperative transmission with the same number of reliable relays in terms of transmission efficiency gain. Furthermore, a Q-learning based cross-layer antenna selection for the multiple-antenna relay networks is proposed, where multiple antennas allow more links from the relays to the destination under time varying Rayleigh fading channel. We studied the performance of multi-antenna relay networks and compared with single antenna case. Both schemes are shown to offer high bandwidth efficiency from low to high signal-to-noise ratios (SNRs). Finally, we conclude that cooperative diversity with learning offers improved performance enhancement and bandwidth efficiency for the communication network.

Acknowledgments

I owe my gratitude to all the people who have helped me through this journey, in one way or another, making this great achievement as much a signicant life experience as a challenging but rewarding intellectual experience.

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Apurba Saha

To my parents for their love and patience

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List of symbols

ρ	Signal to noise ratio
M	Number of low frequency oscillators
y_{sd}	Received signal from source to destination
y_{sr}	Received signal from source to relay
y_{rd}	Received signal from relay to destination
n_{sd}	Additive white Gaussian noise from source to destination
n_{sr}	Additive white Gaussian noise from source to relay
n_{rd}	Additive white Gaussian noise from relay to destination
h_{sd}	Complex channel coefficients from source to destination
h_{sr}	Complex channel coefficients from source to relay
h_{rd}	Complex channel coefficients from relay to destination
E_s	Transmitted energy from source
E_r	Transmitted energy from relay
$\underline{\mathbf{y_{rd}}}$	$(N \times 1)$ Relay to destination receive vector
$\underline{\mathbf{h_{rd}}}$	$(N \times 1)$ Complex channel coefficients vector from relay to destination
$\underline{\mathbf{N_{rd}}}$	$(N \times 1)$ Additive white Gaussian noise vector from relay to destination
P_b	Bit error rate
PER_{sd}	Average Packet Error Rate (PER) of S-D link (direct transmission)
PER_{retx}	Average PER of retransmission
PER_{sr}	Average PER of S-R link
SER_{sd}	Average Symbol Error Rate (SER) of S-D link (direct transmission)
$SER_{RetxRelay}$	Average SER of retransmission
SER_{sr}	Average SER of S-R link
η	Transmission efficiency
T_L	Transmission time for data packet

T_C	Transmission time for CRC packet
P_s	Packet successful probability of reception
$E(T_{packet})$	Average number of packet transmission per packet
$E(T_{Lrelays})$	Average relay selection time per packet
N	Total number of relays
$PER_{RetxRelay}(i)$	Average packet error rate of the i^{th} reliable relay retransmission
L_p	Packet length
$P_r(i)$	Probability that i relays correctly decode the source message
$E(T_{packet})$	Average number of transmissions per packet
$E(T_{Lrelays})$	Average packet retransmission time from the relay
$T_{Lrelays}$	Relay packet transmission time
N_{max}	Maximum number of retransmission
Y_{rd}	$((N_T \times N) \times 1)$ Relay to destination receive vector
N_T	Number of transmit antenna
H_r	$((N_T \times N) \times 1)$ Complex channel coefficients vector from relay's transmit antenna
$E(T_{Lantennas})$	Average packet retransmission from the relay's transmit antenna
$T_{Lrelays}$	Packet transmission time from an antenna

List of Acronyms

ACK	Positive Acknowledgment
AF	Amplify-and-Forward
BER	Bit Error Rate
$BPSK$	Binary Phase Shift Keying
CRC	Cyclic Redundancy Check
CSI	Channel State Information
CTS	Clear to send
$DBPSK$	Difference Binary Phase Shift Keying
DF	Decode-and-Forward
EER	Exploration to Exploitation ratio
$MIMO$	Multiple-Input-Multiple-Output
MRC	maximum ratio combining
$NACK$	Negative Acknowledgment
$O-STBC$	orthogonal space time block codes
RTS	Request to send
$SARSA$	State-Action-Reward-State-Action
SC	Selection Combining
SER	Symbol Error Rate
$SIFS$	Small Inter Frame Space
SNR	Signal-to-Noise Ratio
$TDMA$	Time-Division Multiple-Access

Chapter 1

Introduction

With the explosive growth of wireless communication services (e.g., data, voice, multimedia, e-health, online gaming etc), the performance of communication services has always been a major issue to provide the most enjoyable communications for people than ever expected. But, wireless communications suffer from great challenges due to multipath fading effects of wireless channels. Signals affected by fading can suffer from severe loss of received signal-to noise ratio (SNR) because of deep fading. Based on coherence time or coherence bandwidth of the fading channel, channels can be divided into slow and fast, or flat and frequency-selective fading respectively. In order to combat these fading effects and boost system performance of wireless communications, some techniques known as diversity techniques have been proposed and widely adopted in practice.

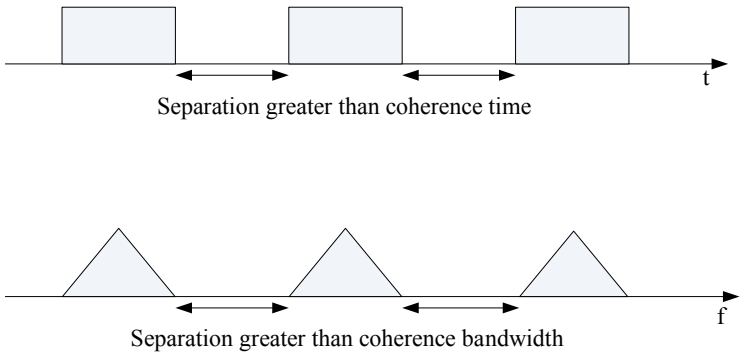


Figure 1.1: Illustration of time and frequency diversity [1]

There are many methods by which diversity can be achieved, example include time diversity, frequency diversity and space (spatial) diversity. Time diversity is achieved by sending same signal several times over the fading channels during different time slots. Difference between time slots has to sufficiently large and should be more than the coherence time of the channel [2], [1]. Frequency diversity is achieved by transmitting same signal over different frequency bands, and difference between these frequency bands should be more than coherence bandwidth of the channel. An Illustration of time and frequency diversity is shown in Fig. 1.1. Among these diversity techniques, spatial diversity is of particular interest because it can be easily combined with the well known multiple-input-multiple-output (MIMO) techniques, where multiple antenna are used to transmit and/or receive the original messages. MIMO technology offers signicant increase in data throughput and link range without additional bandwidth or transmit power [3], [1]. Because of higher spectral efficiency and better link quality, MIMO is an important part of modern wireless communication standards [4], [5] such as IEEE 802.11n (WIFI), 4G, 3GPP, Long Term Evolution, WiMAX and HSPA+.

Full diversity gain can be achieved using MIMO techniques, but employing multiple antennas at the transmitter and the receiver end is expensive. Illustration of MIMO system with multiple antennas for both transmitter and receiver end is shown in Fig. 1.2. Cooperative diversity is a new way of realizing spatial diversity which is widely used in ad-hoc wireless networks and sensor networks. The classic relay models a class of three-terminal communication channels which consist of a source, relay and destination [6]. This technique exploits the broadcast nature of wireless channels. It imitates the performance advancement of MIMO systems and is achieved by transmission through additional relays [7], [8].

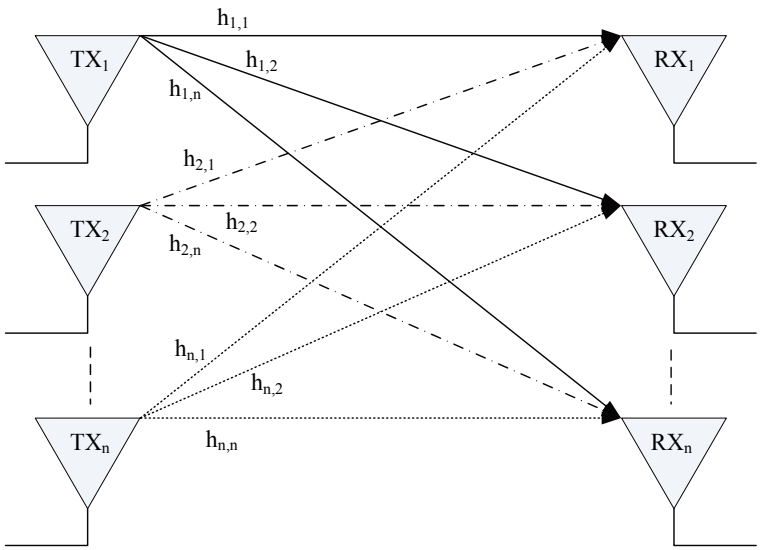


Figure 1.2: Illustration of MIMO channel

1.1 Motivation

Forwarding decoding error at the relay node (the cooperative terminal) to the destination (the receiving terminal) is considered as prominent problem in cooperative systems. Such errors severely degrade the overall performance of the system compared to the direct link transmission. In this case relay selection is required to minimize error propagation from relay node to the destination. Previous works on cooperative communications have been proposed various methods of relay selection to reduce the error propagation and to improve system performance [8]–[11].

In this thesis, we investigate a cross-layer relay selection scheme using machine learning and compare it's performance with previously proposed solutions. Moreover, we also extend our study for cross-layer antenna selection scheme when relays are equipped with more than one transmit antennas.

1.2 Thesis Contributions

Our main contributions of this work can be summarized in the following points.

- We propose a multi-relay cooperative system which works over time-varying Rayleigh fading channel.

- A closed from expression of transmission efficiency of the proposed system is derived and Q-learning based cross-layer relay selection using ϵ greedy mechanism is presented. These relays are those that maximize link layer throughput over Rayleigh fading channel.

- the effect of exploration to exploitation ratio on Q-learning based cross-layer relay selection is also presented. It is shown that frequent exploration degrade the overall system throughput performance.

- A system with multiple transmit antennas at the relay node is introduced. In this system, we employ multiple transmit antenna at the relay nodes. We evaluate the throughput performance with and without transmit antenna selection. Moreover, we compare the results with the single antenna case over the time-varying Rayleigh fading environment for different node speed. We show that, Q-learning based cross-layer transmit antenna selection outperforms the case when all antennas are selected.

1.3 Thesis Outline

The organization of the thesis is as follow: In chapter 2, cooperative networks and various combining techniques are reviewed. We further review Rayleigh fading channel and different combining techniques.

We propose a multi-relay cooperative network over time-varying Rayleigh fading channels in chapter 3. The performance of adaptive decode-and-forward (DF) is studied for learning based cross-layer relay selection. We compare the system performance with the case when all reliable relays are selected to forward the source message to the destination. We also compare the results of the time-varying Rayleigh fading model with independent

Rayleigh fading model.

In chapter 4, we extend the work in chapter 3 to the multi-relay cooperative network where relay nodes are equipped with multiple transmit antennas. We study the performance of the system over time-varying Rayleigh fading channels using the learning based cross-layer transmit antenna selection from the reliable relays. We compare the system performance with the case when the relay nodes are equipped with single antenna.

Finally, chapter 5 presents the thesis conclusions and suggested future works.

Chapter 2

Background

In this chapter, we first present a brief review on cooperative diversity, different diversity combining techniques, Jake's Rayleigh fading model, followed by brief introduction on reinforcement learning. Our intention is to make the reader prepared for next chapters, where we use these techniques in our development.

2.1 Cooperative Diversity

Cooperative diversity has become a popular and attractive alternative solution for MIMO wireless technologies [12], [13]. In cooperative diversity, neighboring nodes assist source node to forward messages to the destination in addition to the direct link between source and destination. By combining source and relay signals, the destination realizes a virtual MIMO system. The two main approaches of cooperative communications are: amplify-and-forward (AF) and decode-and-forward (DF) [8].

2.1.1 Amplify-and-Forward

This method is based mainly on the idea of forwarding an amplified version of the source data to the destination (Fig. 2.1). First the source transmits the data to the

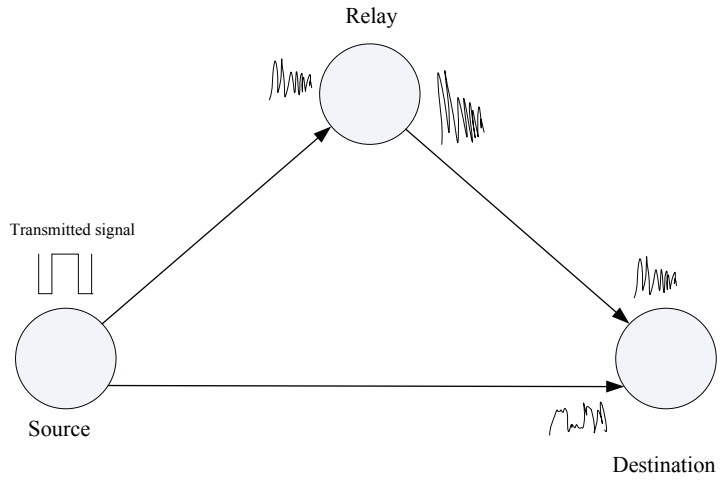


Figure 2.1: Amplify-and-forward cooperation method.

destination and the relay. Then the relay will amplify the received noisy signal of the data and retransmit it to the destination. Finally, the destination receives two independent noisy signals of same data which are then combined to get benefits of space diversity.

2.1.2 Decode-and-Forward

In this mode, the relays decode the source message before re-transmitting the source signal to the destination (Fig. 2.2). Here also at first the source transmits its own message

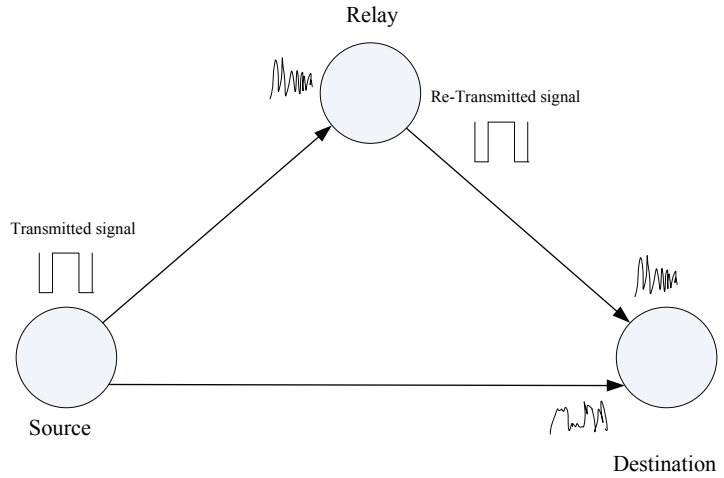


Figure 2.2: Decode-and-forward cooperation method.

to the destination and the relay. Then the relays decode the received signal from the source and retransmit an estimate of the source data to the destination. Finally the destination combines these signals to achieve space diversity. There are several combining techniques that can be used to combine the same data at the destination. In the following section we will consider several combining techniques.

2.2 Diversity Combining Techniques

In diversity techniques the destination receives same data over multiple time slots, where each replica experiences different channel while forwarding to the destination. The idea behind this is that, at least one of the replicas will be received correctly or at least one link has sufficient signal-to-noise ratio (SNR) to decode the transmitted signal correctly. Let us assume we have L replicas (L links) and the probability of error on a single link is p, then the error probability of U independent links is p^L. Therefore, the error rate of the system decreases inversely with the L^{th} power of average SNR. In this case, the system has L order diversity. In diversity combining, Selection Combining (SC), Maximal Ratio Combining (MRC) are two common techniques. In the next subsection we will review these two combining techniques.

2.2.1 Maximum Ratio Combining (MRC)

Let us consider a communication system when L diversity links are available at the receiver. Then the set of received signals at the receiver can be written as

$$y_1 = \sqrt{\rho} h_1 x + n_1$$
$$y_2 = \sqrt{\rho} h_2 x + n_2$$
$$.$$
$$.$$
$$.$$

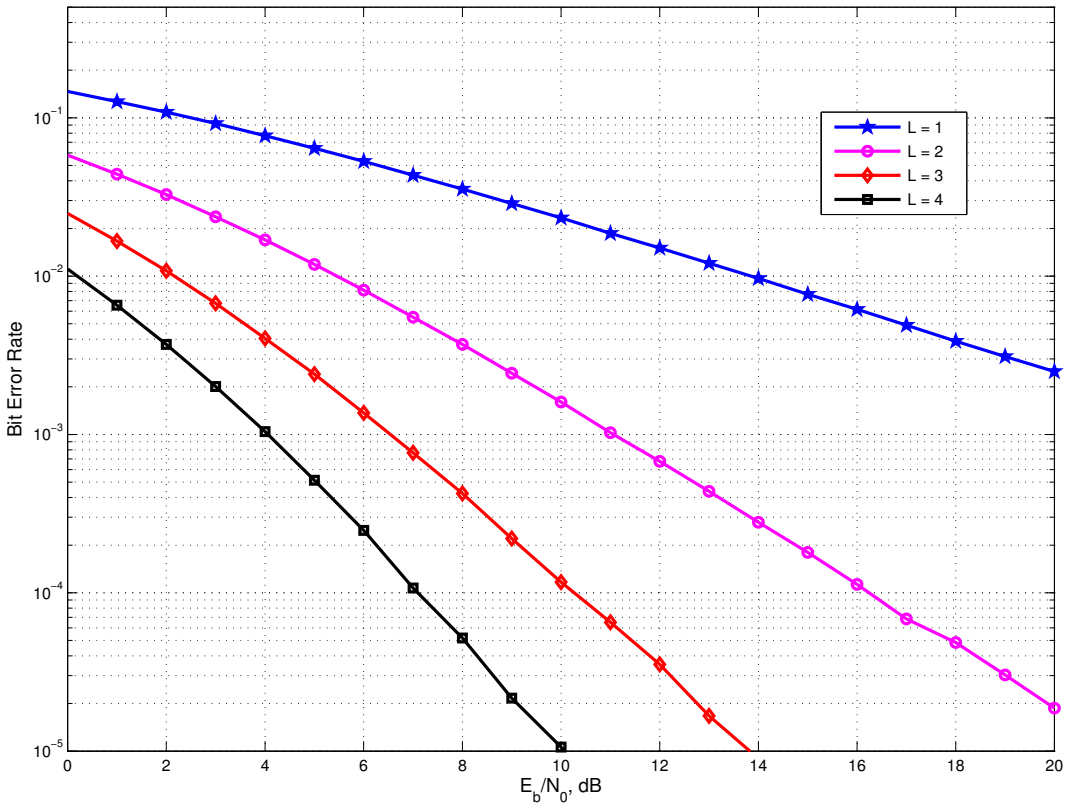


Figure 2.3: Bit error rate of BPSK modulation with MRC in Rayleigh fading channel.

$$y_L = \sqrt{\rho} h_L x + n_L.$$

where the channel gain for the L^{th} link is given by h_L, and the independent Gaussian noise term is denoted by n_L. The average signal to noise ratio per link is ρ. The set of received signals can be combined using MRC when channel knowledge are perfectly available at the receiver. Therefore the received signal using MRC can be written as

$$y = \left(\sum_{j=1}^{L} \left| h_j \right|^2 \right) x + n, \tag{2.1}$$

where n is the Gaussian noise with variance per complex dimension given by $\left(\sum_{j=1}^{L} \left| h_j \right|^2 \right) /2$ [1]. The received effective instantaneous SNR is $\left(\sum_{j=1}^{L} \left| h_j \right|^2 \right) \rho$. This shows that, the SNR of L links with MRC is the sum of each link instantaneous signal to noise ratio. Therefore the error probability performance is decreased.

Figure 2.3, shows the bit error rate of binary phase shift keying (BPSK) modulation over Rayleigh fading channel for different number of links when MRC is used at the receiver. In this case, the fading coefcients are assumed to be known at the receiver. We observe that the error rate performance improves with increasing the number of links.

2.2.2 Selection Combining (SC)

In selection combining, the main idea is to select the best link for a given transmission. Among the L transmissions, only the best link is selected and used for decoding. In SC, we simply measure the received signal power for different links and make the selection based on received signal power. This allowed us to work with one single link, i.e. the best one at a given time. In other words, in SC the link with the highest SNR is selected for demodulation. Therefore, the input-output relationship between the transmitted and received signals is described in [1] as

$$y = \left(\max_{j=1,2,....L} \left| h_j \right| \right) x + n, \tag{2.2}$$

where L is number of links and n is a complex Gaussian random variable with variance 0.5 per dimension. Thus the effective instantaneous SNR after combining is given by [1]

$$\rho_{SC} = \left(\max_{j=1,2,....L} \left| h_j \right|^2 \right) \rho. \tag{2.3}$$

Figure 2.4, shows the bit error rate of BPSK modulation over Rayleigh fading channels for different number of links when SC is used at the receiver. In this case, the fading coefcients are also assumed to be known at the receiver since coherent modulation (BPSK) is used at the receiver. We observe that the error rate performance also improves with increasing the number of links but, an interesting modulation scheme to be used in conjunction with the SC is differential PSK (DPSK). This is because no explicit channel estimation is needed for detection, and selection can be done using the received signal

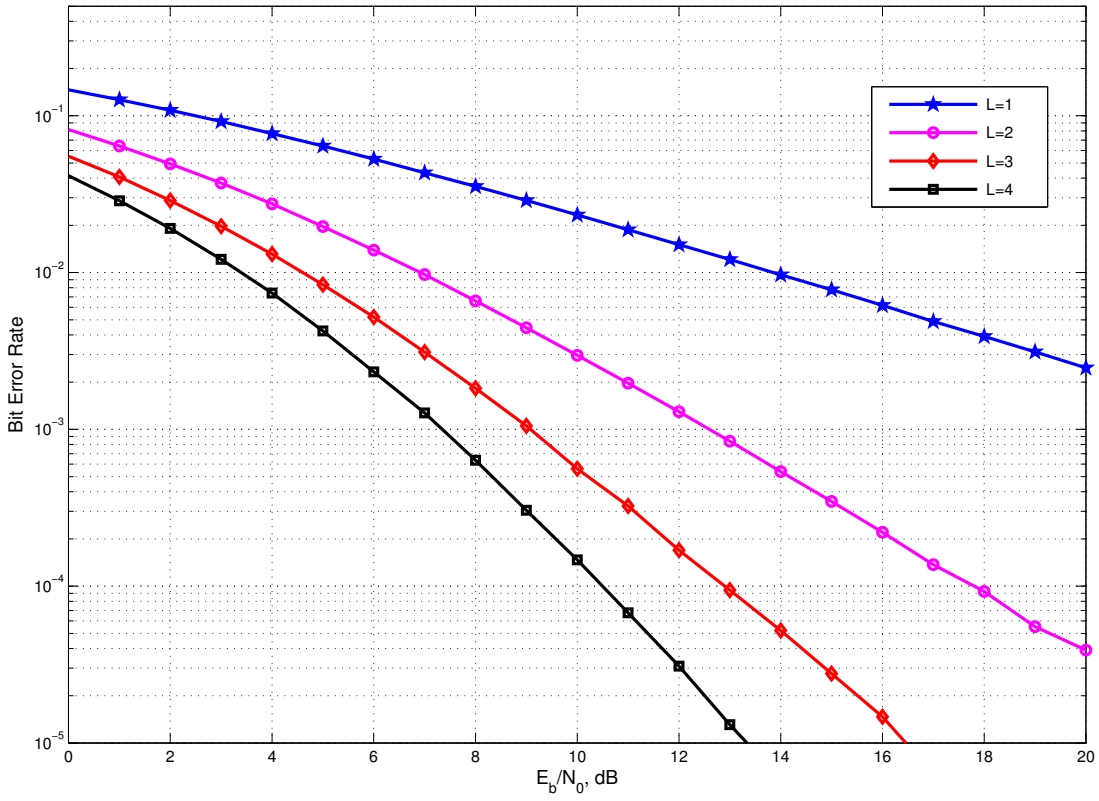


Figure 2.4: Bit error rate of BPSK modulation with SC in Rayleigh fading channel.

power, which may degrade the error performance slightly.

2.3 Jake's Channel Model

Jake's channel model is widely used for modeling a Rayleigh fading Channel. This model allows an effective approximation of the desired Rayleigh fading model by using finite number of low frequency sinusoid oscillators [14]. The complex low-pass Rayleigh fading envelope in [15] can be written as

$$g(t) = g_I(t) + jg_Q(t) \tag{2.4}$$

where

$$g_I(t) = 2\left[\sum_{n=1}^{M} \cos\beta_n \cos 2\pi f_n t + \sqrt{2}\cos\alpha \cos 2\pi f_m t\right] \tag{2.5}$$

$$g_Q(t) = 2\left[\sum_{n=1}^{M} \sin\beta_n \cos 2\pi f_n t + \sqrt{2}\sin\alpha \cos 2\pi f_m t\right]. \tag{2.6}$$

From the above, fading simulator can be constructed as shown in Fig. 2.5. Here M is number of low frequency oscillators with frequency $f_n = f_m \cos(2\pi n/U)$ where $n = 1, 2, ..., M$, and $M = 4U + 2$. The amplitude at each frequency is set to unity except for the frequency f_m which has amplitude $1/\sqrt{2}$.

Note that the channel phases in (2.4) are desired to be uniformly distributed. To achieve this goal, the phases α and β_n are chosen in such a way that $< g_I^2(t) >=< g_Q^2(t) >$ and $< g_I(t)\, g_Q(t) >= 0$, where $< . >$ is a time average operator. From Fig. 2.5, $< g_I^2(t) >$ and $< g_Q^2(t) >$ can be written as [15]

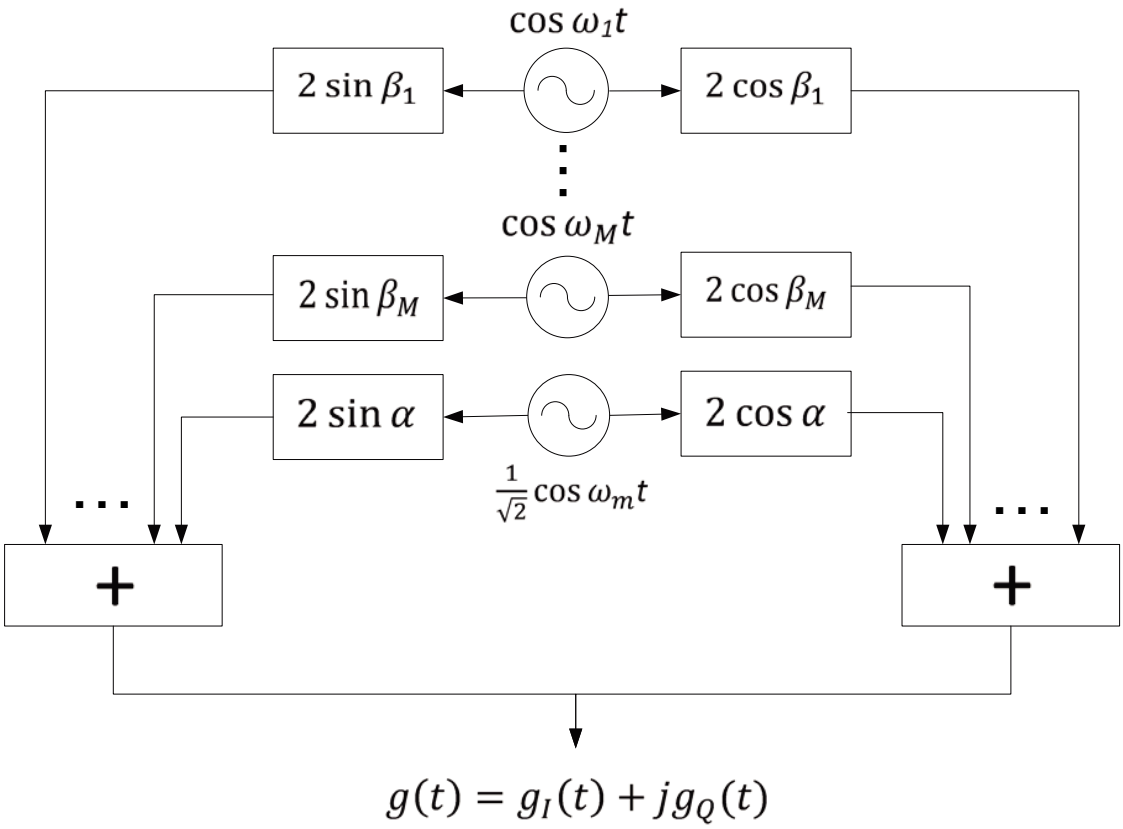


Figure 2.5: Jake's fading genarator by summing a number of low frequency oscillators, where $\alpha = 0$ and $\beta_n = \pi n/M$, gives $< g_I^2(t) >= M + 1$, $< g_Q^2(t) >= M$ and $< g_I(t)\, g_Q(t) >= 0$ [15].

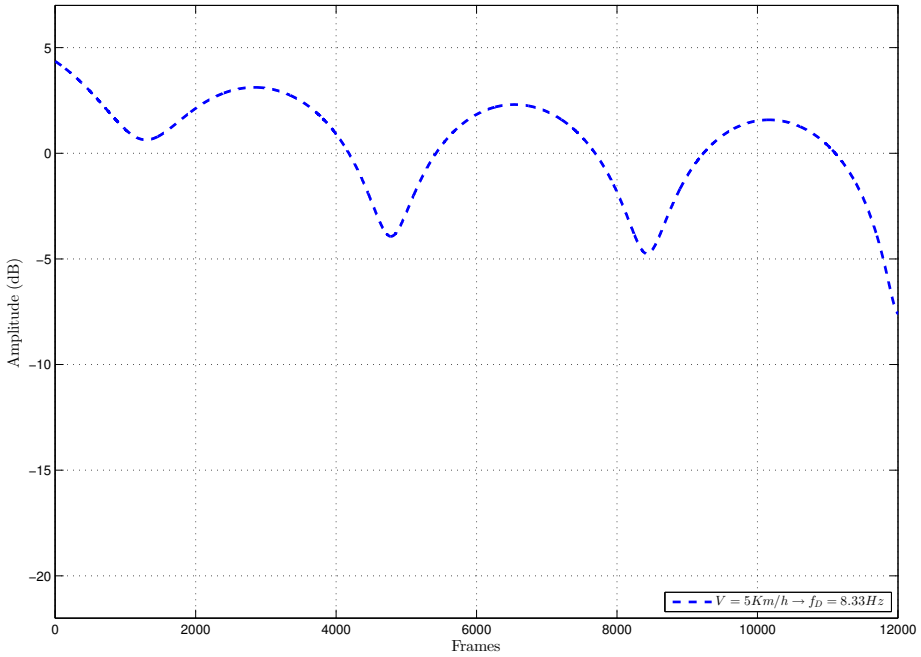


Figure 2.6: Fading envelope when $V = 5km/h$ and maximum Doppler frequency $f_D = 8.33Hz$.

$$< g_I^2(t) > = 2\sum_{n=1}^{M} \cos^2 \beta_n + \cos^2 \alpha \tag{2.7}$$

$$= M + \cos^2 \alpha + \sum_{n=1}^{M} \cos 2\beta_n \tag{2.8}$$

$$< g_Q^2(t) > = 2\sum_{n=1}^{M} \sin^2 \beta_n + \sin^2 \alpha \tag{2.9}$$

$$= M + \sin^2 \alpha + \sum_{n=1}^{M} \cos 2\beta_n \tag{2.10}$$

$$< g_I(t) >< g_Q(t) >= 2\sum_{n=1}^{M} \sin \beta_n \cos \beta_n + \sin \alpha \cos \alpha \tag{2.11}$$

Now by seeting $\alpha = 0$ and $\beta_n = \pi n/M$, yields to $< g_I^2(t) >= M+1$, $< g_Q^2(t) >= M$,

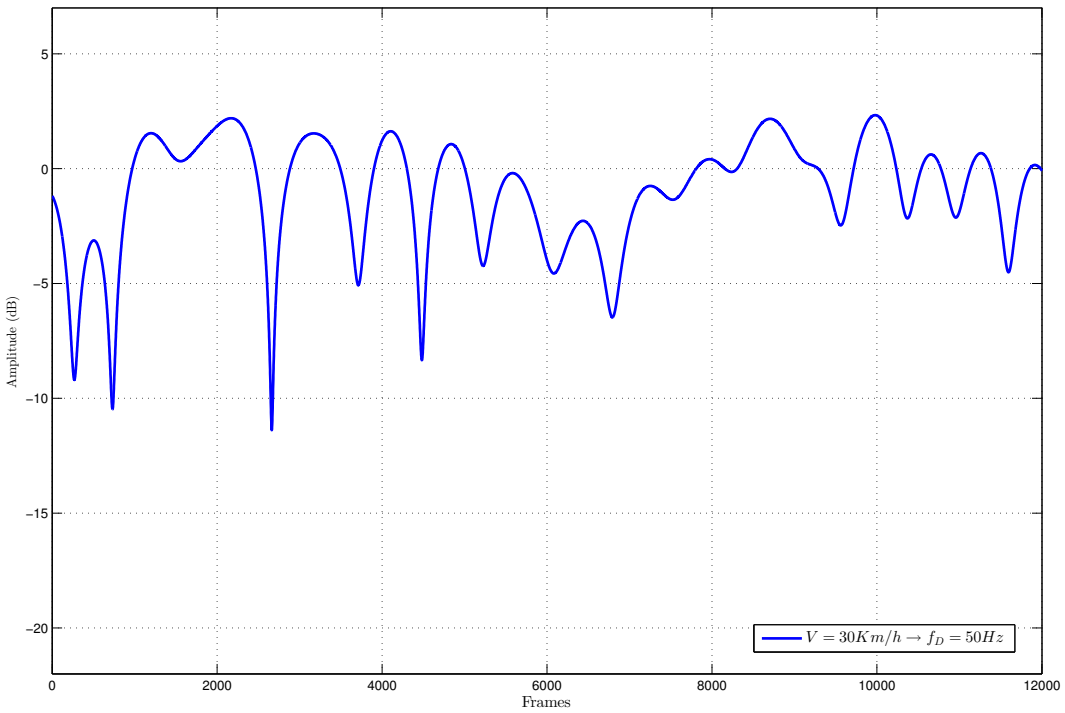


Figure 2.7: Fading envelope when $V = 30km/h$ and maximum Doppler frequency $f_D = 50Hz$.

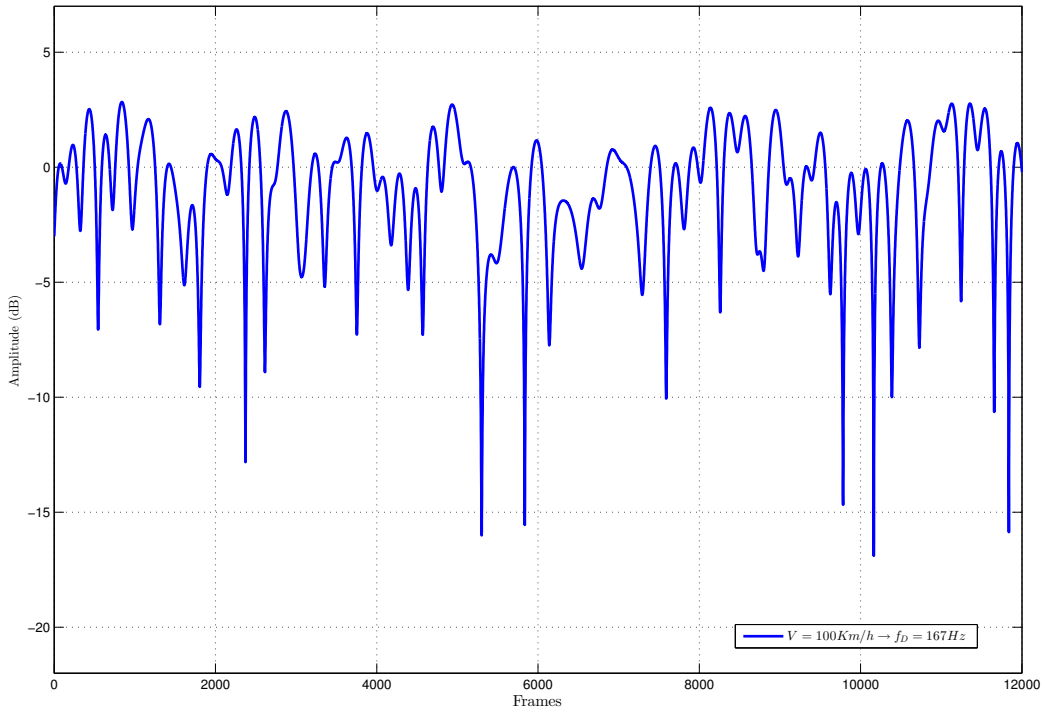


Figure 2.8: Fading envelope when $V = 100km/h$ and maximum Doppler frequency $f_D = 167Hz$.

and $< g_I(t)\, g_Q(t) >= 0$. The mean square value $< g_I^2 >$ and $< g_Q^2 >$ can be selected to any desired value and the Rayleigh fading envelope is obtained by using $U = 34$ or $M = 8$ as shown in Fig. 2.6, 2.7 and 2.8 for different speeds at $V = 5km/h$, $30km/h$ and $100km/h$.

2.4 Reinforcement Learning

In these algorithms the learner is a decision-making agent that takes actions in a environment and receives reward or penalty for its actions in trying to solve a problem. After a set of trial-and-error runs, decision maker should learn the best policy, which is the sequence of actions that maximize the total reward (Fig. 2.9) [16]. The basic

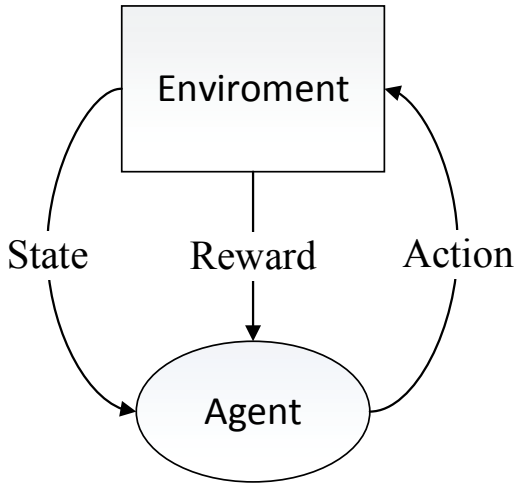


Figure 2.9: The agent interacts with an environment and at any state of the environment agent takes an action that changes the state and returns a reward [16].

reinforcement learning model consists of:

- a set of states S_t
- a set of actions A

- rules of transitioning between states

- rules that determine the scalar immediate reward or penalty of a transition; and

- rules that describe what the agent observes.

In this learning process, an agent interacts with the environment in discrete time steps. At time t, the agent receives an observation o_t, which includes the reward r_a. Based on the reward, the agent chooses an action from the set of available actions which is subsequently sent to the environment. As a result, the environment moves to a new state s_{t+1} and the reward r_{t+1}. In the literature, some of the well known reinforcement learning algorithms are: Temporal difference learning, Q-learning, State-Action-Reward-State-Action (SARSA) [16], Learning automata [17], etc. These algorithms have been applied successfully to problems such as robot control, elevator scheduling, telecommunications.

2.5 Q-Learning

Q-learning is a form of reinforcement learning technique. In this technique, agent learns to find an optimal action-selection policy for any given state. Each state provides reward to the agent for a selected action. The goal of the agent is to maximize the rewards by selecting the best action in each state. In the next few subsections, we briefly describe some factors that effect the Q-learning algorithm.

2.5.1 Learning Factor

The learning factor determines to what extent the recent information will override the past information. The numerical value of learning factor is usually between 0 and 1.

In this case, an agent is not learning when the learning factor is 0 and learning factor 1 leads to the case where the agent considers the most recently acquired information. Learning factor 1 is optimal for deterministic environments and learning factor is 0 when the states are stochastic. But in practice, learning rate is assumed to be constant for all states.

2.5.2 Discount Factor

The discount factor is responsible for the future rewards. A factor value 0 will make the agent use the current rewards only, and a factor that approaches toward 1 will make the agent endeavor for a long-term high reward. If the discount factor equals or greater than 1, the action values may diverge.

2.5.3 Initial Conditions

Q-learning algorithm sets an initial condition before first update occurs, since it is an iterative algorithm. Initial condition is set in such a way that it encourage exploration. In exploration, the algorithm chooses random action and updates the Q-learning table using the reward from the environment. Otherwise the algorithm chooses an action associated with the highest Q-value in the Q-learning table.

2.6 Cognitive Radio

The worldwide technical advancement in mobile wireless communication and the increasing number of mobile users, mobile devices such as cell phones, PDAs and laptops have made a revolutionary change in the genus wireless communication. On the other hand, Federal Communication Commission (FCC) measurements reveal that, current spectrum utilization efficiency of the licensed radio spectra could be as low as 15% on average [18]. To address this inefficiency of radio spectrum usage, the FCC has motivated

the use of opportunistic spectrum sharing to make the licensed frequency bands accessible for unlicensed wireless users. The main objective behind this is to create cognitive competence of wireless devices for both licensed and unlicensed spectrum usage.

For increasing the efficiency of the spectrum usage, secondary (unlicensed) user determines available frequency channels and respective bandwidths by using spectrum-sensing capability. After successful sensing of opportunity, non-utilized frequency channels are assigned to cognitive radios (CR). Simultaneous spectrum-sensing and data transmission causes degradation of Quality of service (QoS). Under this constraint two design objectives can be considered namely, spectrum Sensing optimization and to achieve desired level of QoS. To meet these design objectives, performance metric of overall system should be maximized. Two important performance metrics in spectrum sensing should be considered, the probability that a CR falsely detects a primary user (PU) when no PU is present and the probability that a CR fails to detect a PU when it is present.

So far, most of the studies are focused on policy based radio, where a list of rules are assigned for the radios to behave in a certain situation. Machine learning is a technique that can be incorporated with CR to improve the system performance. Reinforcement learning can be used in unknown environment, where an agent learns from trail-an-error [19], [16]. Dynamic channel allocation using reinforcement learning has been studied in [20]. Moreover, in [21] adaptive transmit power for spectrum management and in [22] cooperative sensing in CR ad-hoc networks have been studied using reinforcement learning. Efficient exploration in reinforcement learning for CR spectrum sharing has been studied in [23]. Other learning techniques, game theory, neural networks are also studied in the context of CR [24].

CR with multiple antennas should be chosen for more powerful spectrum sensing schemes [25]. CR with multiple antenna and machine learning techniques have been studied for environment learning in [26]. MIMO with CR utilizes simultaneous spectrum-sensing and data transmission using multiple antenna technology to increase the through-

put of CR systems and avoid delay caused by spectrum sensing.

2.7 Cognitive Networks

A cognitive network can be described as a cognitive process that can realize the current network conditions, and then plan, decide, and act on those conditions. This network can learn from these adaptations and use them for the future decisions, by considering end-to-end performance goals. Cognition can be used to improve the performance of resource management, QoS, security, access control, or many other network performance goals compare to noncognitive networks. In most of the cases, implementing a cognitive network requires a system that is more complex than a noncognitive network. At the same time, cognitive network is costly in terms of overhead, architecture, and operation that should justify the overall performance of the network [27]. In cognitive networks, goals are based on end-to-end network performance but in the case of cognitive radio goals are depended on only the radio user. This end-to-end performance goal helps the cognitive network to operate in all layers of protocol stack. Another main difference is cognitive networks are applicable both wired and wireless networks, whereas cognitive radios are applicable only in wireless networks.

In this thesis, we propose cross-layer schemes that target cognitive networks as it is based on learning techniques.

2.8 Conclusions

In this chapter, we have presented an overview for cooperative relay networks, several diversity techniques, reinforcement learning, Rayleigh fading channel model, Q-learning, cognitive radio, and cognitive networks. For the remaining chapters, we will be using these protocols and mathematical tools to address the relays and antennas selection issues of cooperative relay networks.

Chapter 3

Learning Based Relay Selection

3.1 Introduction

As an alternative of multiple antennas, cooperative diversity system allows the receiver to see independent versions of source's information which yield to realize the spatial diversity without increasing the total transmit power. The two main modes of cooperative communications are: regenerative or DF and non-regenerative or AF. In AF mode, relay node amplifies the source message prior forwarding to the destination, whereas in DF mode the relay decodes the source message and re-generates an estimate of this message before forwarding to destination.

From the standpoint of DF, decoding errors occurring at relay node(s) cause severe performance degradation in terms of symbol error rate (SER) compared to the direct link transmission. In this case, the system suffers from detrimental effects due to error propagation when the channel between the source and relay (S – R) is poor. In these circumstances, relay selection is required to minimize error propagation from relay nodes to the destination. Various methods have been proposed to reduce the error propagation and to improve the system performance [8], [9]. For instance in [8], relay node(s) only forward the source message if the S – R channel gain is above given threshold level. It is

shown in [28] that only relays with correctly decoded messages forward source message to the destination. Other relay selection schemes where relay is selected based on maximum SNR between relay and the destination are presented and analyzed in [10]– [11]. In [29] the authors have shown that using media access control (MAC) layer RTS-CTS signaling, best relay can be selected based on minimization of energy consumption.

In relay networks, selecting all reliable relay(s) is not the optimal solution for the overall performance enhancement. Recently, many works have focused on cross-layer design approaches for relay networks. In [9], the authors presented throughput maximization scheme based on packet and modulation size optimization, where both source and reliable relays realize orthogonal space time block codes (O-STBC). The work in [9] also showed that throughput performance can be further improved through packet length and modulation size optimization. Relay combination can also be chosen through machine learning method, where selection is performed using past relay selection experience at the destination.

Recently, many studies have been conducted using machine learning in cognitive radio systems. In [30], [31] game-theoretic stochastic learning is used to address the problem of distributed channel selection for opportunistic spectrum access. Q-learning is another algorithm in machine learning that belongs to reinforcement learning [16], [32]. In [33] decentralized Q-learning is used to manage aggregated interference control in cognitive radio networks. Q-learning is also used for relay selection based on physical layer parameters in [34]. Motivated by the works in [9], [33]– [35], we propose a cross-layer relay selection scheme using Q-learning that maximizes the link layer throughput. Another advantage of the proposed scheme is the average relay utilization to ensure efficient use of the available bandwidth. In [9], all reliable relays are selected to forward the source's message to destination, whereas our proposed scheme always select less number of relays compared to the scheme in [9].

The rest of the chapter is organized as follows. In section 3.2, the system model

is described. Derivation of transmission efficiency, the proposed relay selection algorithm using Q-learning and simulation results are presented in section 3.3, 4.4, 3.5, respectively. Finally conclusions are outlined in section 3.6.

3.2 System Model

We consider a cooperative diversity network consisting of a source, N relays, and a destination as shown in Fig. 3.1. In this scheme, source node transmits a packet to the destination node with cyclic redundancy check (CRC) bits appended to its message for error detection. All relay nodes overhear the transmission due to the broadcast nature of the channel. After receiving a packet, the destination and relays decode the source's message and check for errors. If the destination correctly decodes the source's message, then it sends a positive acknowledgment (ACK) to the source and relays, through a error free feedback channel which is assumed to be perfect. Otherwise, the destination sends negative acknowledgment (NACK) and R_SEL (relay select) packet, requesting for retransmission. When a positive ACK is received, the source transmits a new packet and all relays remain silent. On the other hand when NACK and R_SEL are received, all selected reliable relay(s) forward source information to the destination. Fig. 3.2 and 3.3 show the time diagram and complete flow chart of the system respectively. Finally the destination decodes the combined signal from source and relay(s) nodes.

The retransmission process continues until the destination correctly decodes the source's message or the number of retransmissions reaches its maximum N_{max}. We assume that the source, relays and destination are equipped with single antenna, packets are sent through Time Division Multiple Access (TDMA) communication mode over multipath time-varying Rayleigh fading channels modeled using Jake's model. This model is widely accepted for modeling the time variations of Rayleigh fading channels. We use this model to make better decisions on relay selection using the Q-learning algorithm. This algorithm

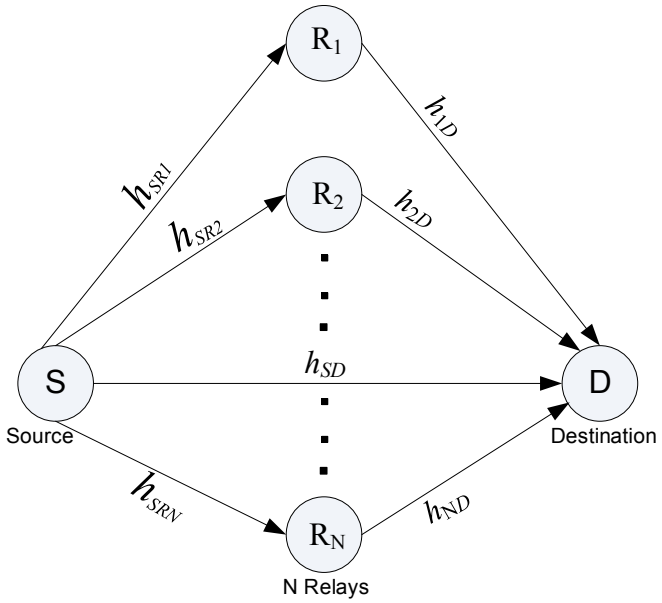
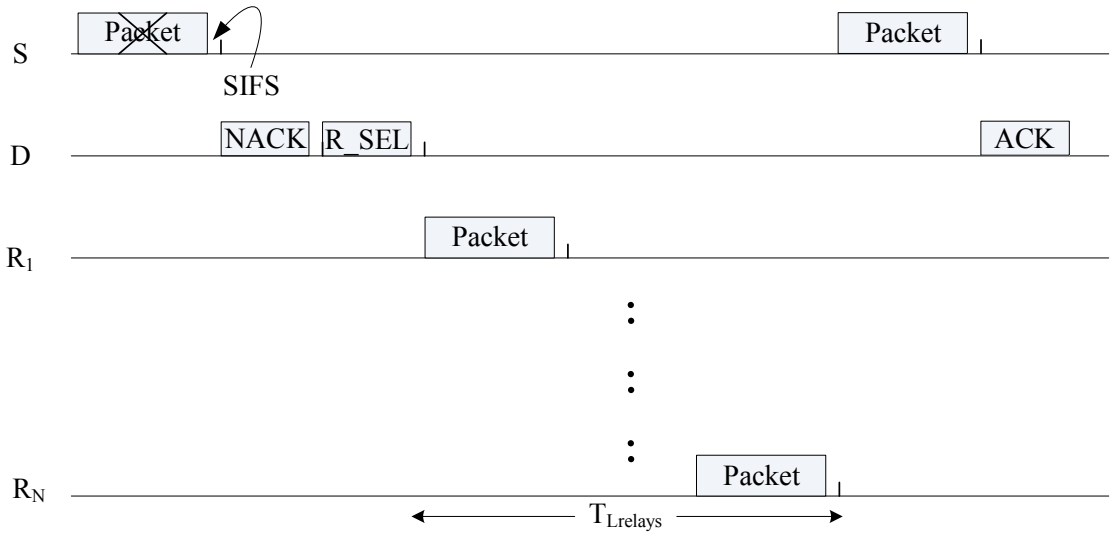


Figure 3.1: Cooperative system with N relays.



R_SEL = Relay Selection SIFS = Small Inter Frame Space

$T_{Lrelays}$ = Packet Transmission Time for Relays

Figure 3.2: Relay selection timing diagram

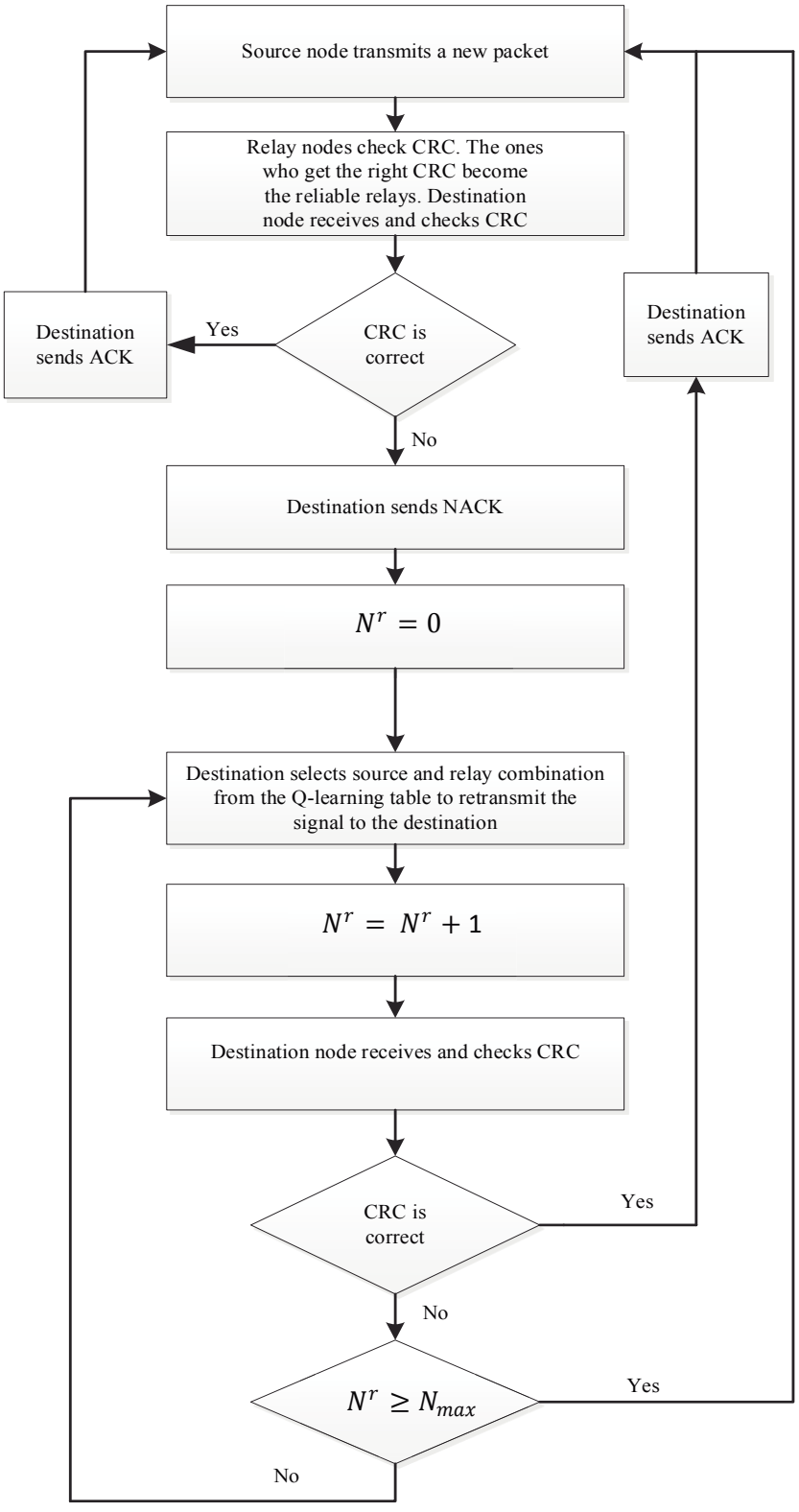


Figure 3.3: Flow chart of the proposed system.

selects the best source and relay combination that maximize the transmission efficiency by selecting either exploration or exploitation modes of operation. For simplicity, we also assume channels are fixed for the entire duration of a packet transmission.

The complex channel coefficients of the source to destination (S-D), source to relay (S-R) and relay to destination (R-D) links are denoted as h_{sd}, h_{sr} and h_{rd}, respectively, each modeled as complex Gaussian distributed with zero mean and unit variance. We also denote the received signal from source to relay, source to destination and relay to destination as y_{sd}, y_{sr} and y_{rd} respectively. These received signals are given by,

$$y_{sd} = \sqrt{E_s} h_{sd} x + n_{sd}, \tag{3.1}$$

$$y_{sr} = \sqrt{E_s} h_{sr} x + n_{sr}, \tag{3.2}$$

$$y_{rd} = \sqrt{E_r} h_{rd} \hat{x} + n_{rd}, \tag{3.3}$$

where x is the transmitted source symbol and $\hat{x}$ is the estimated symbol at the relay. E_s and E_r denote the transmitted energy from source and relay respectively, the noise n_{sd}, n_{sr}, and n_{rd} are additive white Gaussian each with zero mean and variance σ^2. Considering all relays, the received signal at the destination in a vector form is given by,

$$\underline{\mathbf{y_{rd}}} = \sqrt{E_r} \underline{\mathbf{h_{rd}}} \hat{x} + \underline{\mathbf{N_{rd}}}, , \tag{3.4}$$

In (3.4), $\underline{\mathbf{y_{rd}}}$, $\underline{\mathbf{h_{rd}}}$, and $\underline{\mathbf{n_{rd}}}$ are $(N \times 1)$ vector. These are given by,

$$\underline{\mathbf{y_{rd}}}^{\top} = \begin{bmatrix} y_1 & y_2 & ..... & y_N \end{bmatrix}, \tag{3.5}$$

$$\underline{\mathbf{h_{rd}}}^{\top} = \begin{bmatrix} h_1 & h_2 & ..... & h_N \end{bmatrix}, \tag{3.6}$$

$$\underline{\mathbf{N_{rd}}}^{\top} = \begin{bmatrix} n_1 & n_2 & ..... & n_N \end{bmatrix}. \tag{3.7}$$

In the literature, most of the studies consider perfect channel state information (CSI) at the receiver for coherent detection. Here we use non-coherent differential Binary Phase Shift Keying (DBPSK) to overcome the problem of channel estimation at the receiver side and hence lower complexity. This also reduces the communication overhead and wasted power as in pilot and training based channel estimation techniques, specially when the fading is rapid. Non-coherent detection for cooperative communications was studied in [36–38]. To avoid CSI estimation we employ selection combining (SC) technique to combine the signals from source and relays. The performance of SC is inferior compared to the maximum-ratio combining (MRC). However, the implementation of MRC requires knowledge of instantaneous channel gain which as mentioned earlier could be impractical in some scenarios. The conditional bit error rate (BER) for a given channel coefficient h when DBPSK modulation is used can be written as [2],

$$P_b(h) = \frac{1}{2}\exp^{-\rho}. \tag{3.8}$$

where ρ is average signal-to-noise ratio (SNR) per link.

3.3 Performance Analysis

First we define some useful parameters that will be used to evaluate the transmission efficiency (i.e. normalized throughput) of the proposed system.

- PER_{sd} = Average Packet Error Rate (PER) of S-D link (direct transmission).
- PER_{retx} = Average PER of retransmission.
- PER_{sr} = Average PER of S-R link.
- SER_{sd} = Average Symbol Error Rate (SER) of S-D link (direct transmission).
- $SER_{RetxRelay}$ = Average SER of retransmission.

- SER_{sr} = Average SER of S-R link.

The transmission efficiency for adaptive DF is described in [9] as

$$\eta = \frac{(T_L - T_C)P_s k}{T_L E(T_{packet})}, \tag{3.9}$$

where T_L and T_C are the transmission time of data packet and CRC bits, respectively. Packet successful probability of reception and average number of packet transmission per packet are given by P_s and $E(T_{packet})$, respectively. k is number of bits per symbol. However, in [9] the authors did not consider packet transmission time from relay to destination indicated in Fig. 3.2. For that, the link layer transmission efficiency when considering packet transmission time from relay to destination can be rewritten as

$$\eta = \frac{(T_L - T_C)P_s k}{T_L E(T_{packet}) + E(T_{Lrelays})}, \tag{3.10}$$

where $E(T_{Lrelays})$ is the average relay selection time per packet. Now,the packet successful probability of reception P_s is given by [9],

$$P_s = \sum_{i=0}^{N} \left(1 - PER_{sd}\left(PER_{RetxRelay}(i)^{N_{max}}\right)\right) P_r(i), \tag{3.11}$$

where N is the total number of relays, $PER_{RetxRelay}(i)$ denote average PER of the i^{th} reliable relay retransmission given by

$$PER_{RetxRelay}(i) = 1 - (1 - SER_{RetxRelay}(i))^{\frac{L_p}{k}} \tag{3.12}$$

L_p is packet length. When non of the relays could decode the source signal correctly, which is the case when $i = 0$, the average $PER_{RetxRelay}(0) = 1 - (1 - SER_{RetxRelay}(0))^{\frac{L}{k}}$ and $SER_{RetxRelay}(0) = SER_{sd}$. $P_r(i)$ is the probability that i relays correctly decode the

source message and is expressed as [9]

$$P_r(i) = \binom{N}{i} (1 - PER_{sr})^i (PER_{sr})^{N-i}, \tag{3.13}$$

where $i = 0, 1..., N$. $PER_{sr} = (1 - SER_{sr})^{\frac{L_p}{k}}$, and the average number of transmissions per packet $E(T_{packet})$ is given by

$$E(T_{packet}) = \sum_{i=0}^{N} V(i) P_r(i), \tag{3.14}$$

$$V(i) = 1 - PER_{sd} + PER_{sd} \Bigg[\sum_{j=2}^{N_{max}} jPER_{RetxRelay}(i)^{j-2} (1 - PER_{RetxRelay}(i)) (1 + N_{max}) PER_{RetxRelay}(i)^{N_{max}-1} \Bigg]. \tag{3.15}$$

Similarly, $E(T_{Lrelays})$ is the average packet retransmission time for a packet sent to the destination, and is given by

$$E(T_{Lrelays}) = \sum_{i=0}^{N} iV_{Lrelays}(i) P_r(i), \tag{3.16}$$

$$V_{Lrelays}(i) = T_{Lrelays} PER_{sd} \Bigg[\sum_{j=2}^{N_{max}} jPER_{RetxRelay}^{j-2}(i) (1 - PER_{RetxRelay}(i)) (1 + N_{max}) PER_{RetxRelay}(i)^{N_{max}-1} \Bigg], \tag{3.17}$$

where $T_{Lrelays}$ is the relay packet transmission time. Next section, we present our proposed Q-learning algorithm to improve the transmission efficiency.

3.4 Relay Selection Using Q-learning

In the underlying system, the destination adopts Q-learning algorithm. In this algorithm, after a set of trial-and-error, the destination should learn the best policy, which is a sequence of actions that maximize the total reward when channels are modeled as time-varying Rayleigh fading. For our system, an action is defined as packet transmission process through possible source and selected reliable relay(s) combination and the reward is defined as the transmission efficiency for a selected action. In the Q-learning algorithm, the destination selects an action by exploration or exploitation. Here the main goal, is to find a balance between exploration and exploitation.

In the exploration mode of the Q-learning, the destination selects a combination where all reliable relays are present so that the destination can update all possible source and relay combinations. It is to be noted that all relays access the channel using TDMA mode to forward the source message to the destination. On the other hand, in the exploitation mode, the destination selects an action that has the maximum Q-value in the Q-learning table.

The Q-table is used at the destination to store and update the Q-value for different combinations of source and reliable relay(s). A single element subset w_r is chosen from set W_r and can be written as

$$W_r = \{\{SR_1\}, \{SR_2\}, \{SR_3\}, ..., \{SR_1R_2...R_N\}\}. \tag{3.18}$$

For example, SR_1 is defined as a single element subset of W_r when only the source(S) and relay(R_1) are used for packet transmission. Now, we define a as an action for which the destination receives a reward r_a. Reward can be calculated from (3.10) and the Q-value $Q_t(a)$ is estimated after an action a at time t. The Q-values are updated according to following function given by [16],

Table 3.1: Q-learning Table For Relay Selection

$Time$	$Q(SR_1)$	$Q(SR_2)$	..	$Q(SR_n)$	..	$Q(SR_1R_2..R_N)$
0	0	0	..	0	..	0
..	..	..	..	..	..	..
..	..	..	..	..	..	..
..	..	..	..	..	..	..
t_1	$Q_{t_1}(SR_1)$	$Q_{t_1}(SR_2)$	..	$Q_{t_1}(SR_N)$	..	$Q_{t_1}(SR_1R_2..R_N)$
t_1+1	$Q_{t_1+1}(SR_1)$	$Q_{t_1+1}(SR_2)$	..	$Q_{t_1+1}(SR_N)$	..	$Q_{t_1+1}(SR_1R_2..R_N)$

$$Q_{t+1}(a) = Q_t(a) + \eta\left[r_{t+1}(a) - Q_t(a)\right], \tag{3.19}$$

where η is the learning factor and $r_{t+1}(a)$ is the reward at time $t+1$ for action a. $Q_{t+1}(a)$ is the expected value for action a at time $t+1$. Initially, we set all values of the Q-table to zeros. After that, the destination chooses an action by exploration or exploitation. For the selected action, the destination receives a reward ($r_a \geq 0$) after which it evaluates its Q-value to update the Q-table.

Table 3.1 shows the Q-table where we can see that all Q-values are initialized to zeros at initialization. For instance, we assume that at time t_1+1 a single element subset SR_N is selected by exploitation because the Q-value of the single element subset SR_N has maximum Q-value among all elements in the Q-table at time t_1. In Table 3.1, $Q_{t_1+1}(SR_N)$ and $Q_{t_1}(SR_N)$ represent the Q-value at time $t+1$ and t, respectively. At time t_1+1, $Q_{t_1}(SR_N)$ is updated by $Q_{t_1+1}(SR_N)$ and the remaining Q values are kept unchanged. In this process, the destination does not need CSI information for relay selection. That is no overhead incurred by the system where all reliable relays do not need to send extra bits to estimate the CSI for relay selection.

3.5 Simulation Results

In this section, we present simulation results to assess the performance of the adaptive DF cooperative system using the proposed Q-learning relay selection scheme.

We investigate the transmission efficiency and usage of relay combination under different time-varying Rayleigh fading channels. The simulation parameters are as follows, packet transmission time and CRC bits transmission time are $T_L = 2.667 \times 10^{-4}$s and $T_C = 4.167 \times 10^{-6}$s, respectively. It is to be noted that the packet length is set to 1024 bits, CRC is 16 bits long and the corresponding transmission data rate is $3.84 \times 10^6 bps$. The maximum number of retransmissions per packet $N_{max} = 3$ and unless otherwise specified, the total number of available relays is N= 4 and the average SNR of the source to relay(s) link is $\gamma_{s-r} = 20$dB. The channels are modeled as Rayleigh fading with fading coefficients fixed for the entire duration of the packet transmission.

3.5.1 Q-learning Based Relay Selection Using ϵ Greedy Mechanism

In this subsection, Q-learning algorithm selects a source and reliable relay(s) based on ϵ greedy mechanism presented in [39]. In this mechanism, the destination chooses exploration with probability ϵ and selects an action that has maximum Q-value in the Q-learning table (Q-table) with probability $(1-\epsilon)$. The destination starts the exploration with a very high ϵ value and updates ϵ after each successful packet transmission as in (3.20),

$$\epsilon = \epsilon - \frac{\epsilon}{m_r}. \tag{3.20}$$

where m_r is update parameter. From (3.20), we can write the probability of selecting a source and relay combination as

$$z_i = \begin{cases} 1 - \dfrac{\epsilon}{m_r}, & \text{if the action is exploitation} \\ \dfrac{\epsilon}{m_r}, & \text{otherwise} \end{cases} \tag{3.21}$$

In our simulation, we set the update parameter m_r in such a way that the destination chooses exploration frequently. It is noted that exploration helps the destination

Algorithm 1 Q-learning algorithm for relay selection using ϵ greedy mechanism

ϵ = Probability of choosing exploration
rv = Uniformly distributed [0,1]
for (initial time to end time) **do**
  $\epsilon = \epsilon$/update parameter
  $p = \epsilon$
  if $p < rv$ or $\epsilon ==$ initial value **then**
    Choose source and relay combination where all reliable relays are present
  else
    Choose source and relay combination associated with the highest Q-value in the Q-table
  end if
  if $\epsilon > 1$ **then**
    ϵ to initial value
  end if
  Update Q-table using (3.19)
end for

Table 3.2: Transmission Efficiency for Different Update Parameter When $V = 5km/h$, $V = 30km/h$ and $V = 100km/h$. $\gamma_{r-d} = 8$dB

Update Parameter (m)	Transmission Efficiency ($V = 5km/h$)	Transmission Efficiency ($V = 30km/h$)	Transmission Efficiency ($V = 100km/h$)
0.75	0.3797	0.3922	0.3898
0.80	0.3797	0.3922	0.3898
0.85	0.3797	0.3922	0.3898
0.90	0.3797	0.3922	0.3898
0.95	0.3797	0.3922	0.3898

to make good decision on relay selection. Algorithm 1 summarizes this source and relay combination selection protocol.

Table 3.2 shows the transmission efficiency for different values of update parameter for node speeds $V = 5km/h$, $30km/h$, and $100km/h$. In these results, we set $\gamma_{s-r} =$ 20dB and the SNR of other links are set to 8dB. It can be observed that the change of update parameter has no effect on the transmission efficiency. This implies that frequent exploration at destination results almost in the same throughput with the change of update parameter.

Figs. 3.4–3.6 show the transmission efficiency comparison between our proposed

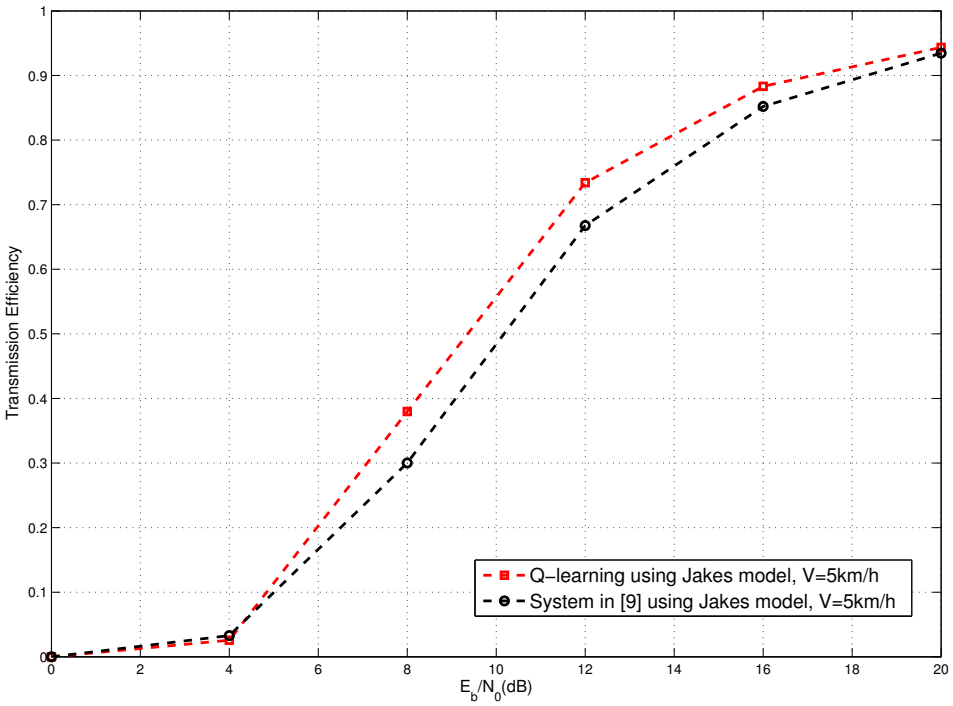


Figure 3.4: Transmission efficiency comparison of system in [9] and Q-learning using ϵ greedy mechanism, under Jake's channel model where $V = 5km/h$, γ_{s-r} =20dB.

system using Q-learning and ϵ greedy mechanism with the system in [9]. To do that, we set the number of relays and channel gains to be identical for both schemes. It is to be noted that the system in [9] considers all correctly decoded relays to forward the source message to the destination. On the other hand, in our proposed system, relays are selected based on the relay selection criteria presented in Algorithm 1. From the results, we can see that our system provides better performance in most of the cases, which implies that relay selection using Q-learning performed at link-layer improves the system performance.

Fig. 3.7 also shows the transmission efficiency comparison between Q-learning based ϵ greedy mechanism under Jake's Rayleigh fading model with $V = 5km/h$, $30km/h$, and $100km/h$ and the case of independent fading realizations. From the results, we can see that both cases perform almost identical from low SNRs to high SNRs, because Algorithm 1 operates in such a way that the destination chooses exploration more than exploitation. Note that, in the independent channel model case, the probability of selecting incorrect

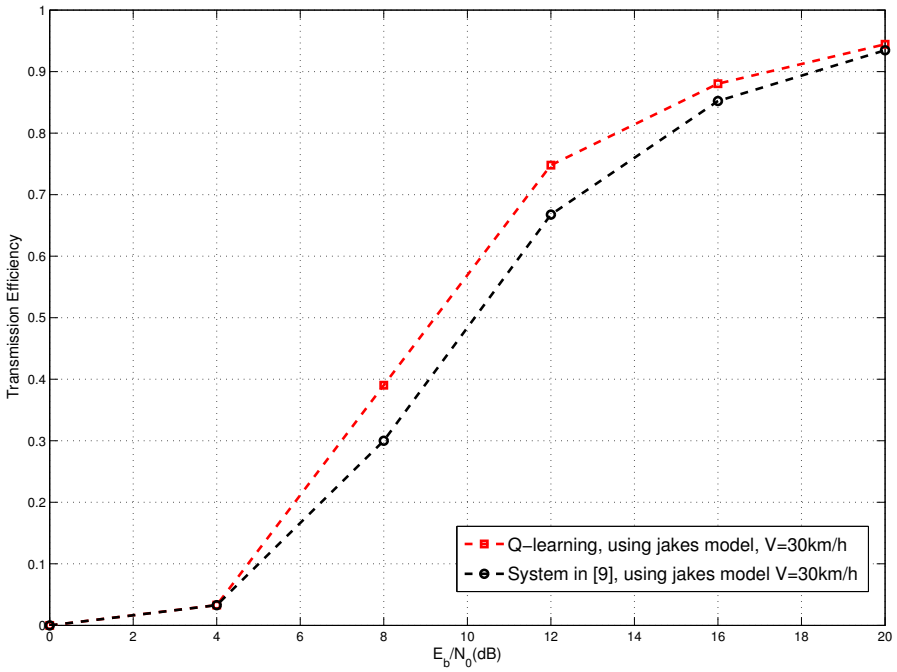


Figure 3.5: Transmission efficiency comparison of system in [9] and Q-learning using ϵ greedy mechanism, under Jake's channel model is used where $V = 30km/h$, γ_{s-r} =20dB.

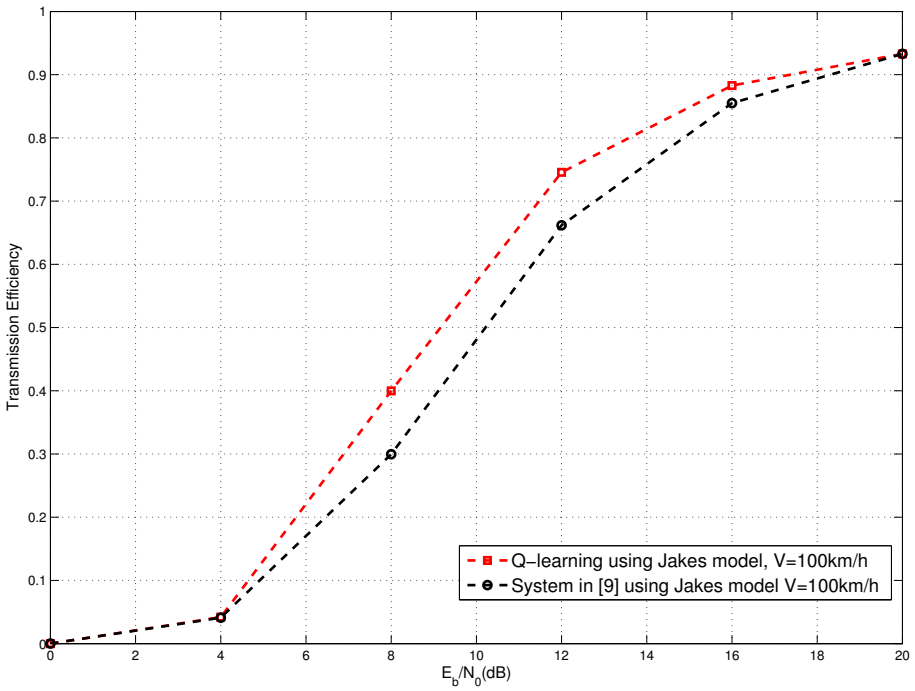


Figure 3.6: Transmission efficiency comparison of system in [9] and Q-learning using ϵ greedy mechanism, under Jake's channel model is used where $V = 100km/h$, γ_{s-r} =20dB.

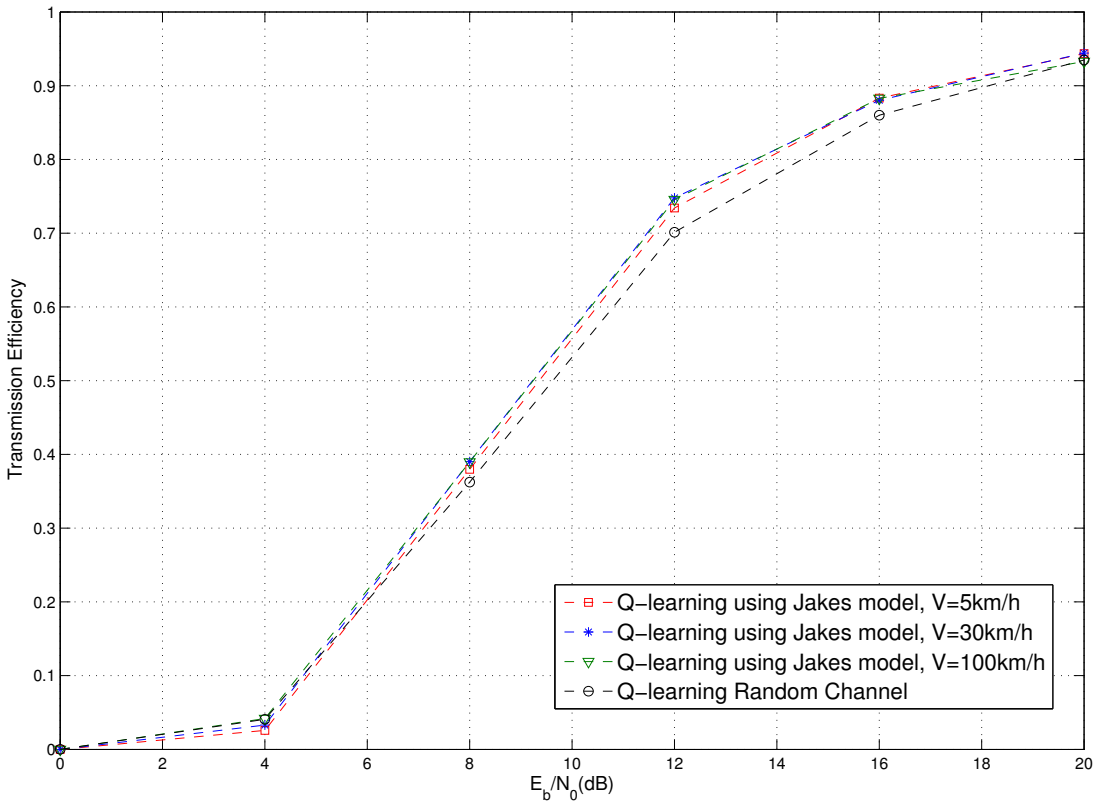


Figure 3.7: Transmission efficiency comparison of Q-learning using ϵ greedy mechanism, under Jake's channel model where $V = 5km/h$, $V = 30km/h$, $V = 100km/h$ and independent fading model with γ_{s-r} =20dB.

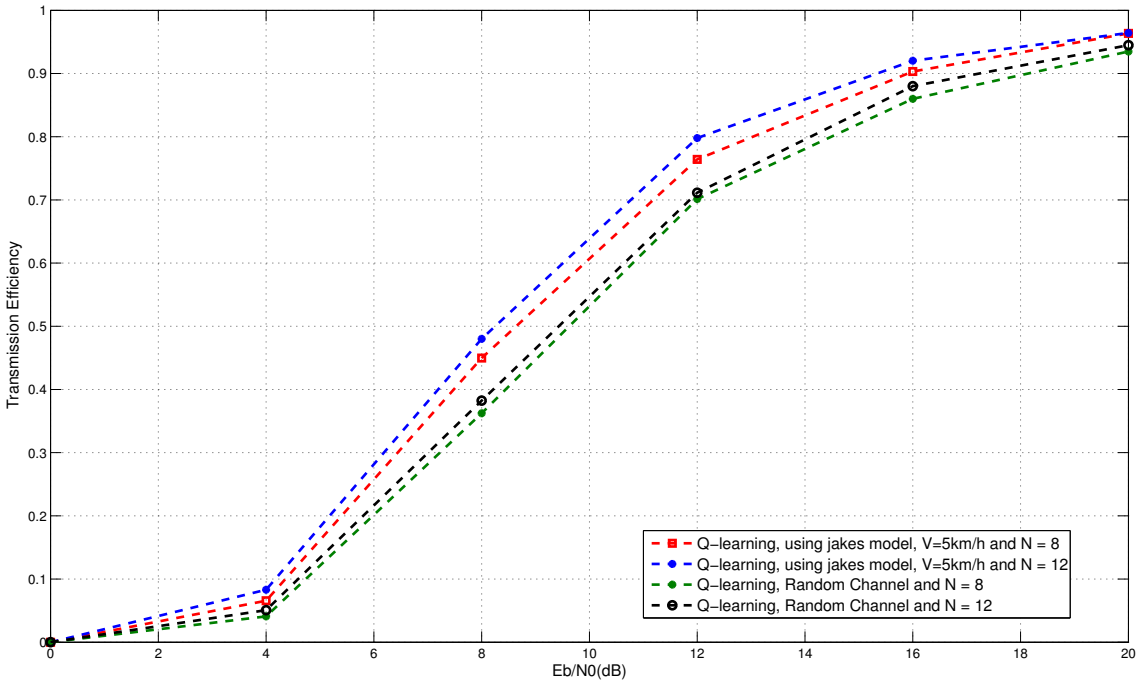


Figure 3.8: Transmission efficiency comparison of Q-learning using ϵ greedy mechanism, under Jake's channel model where $V = 5km/h$ and independent fading model with γ_{s-r} =20dB, N = 8 and 12.

relay combination is small when the number of relays is also small. Another reason is that the Q-learning using ϵ greedy mechanism algorithm is suitable since it learns how many relays are good for maximizing the link layer transmission efficiency. From here we can say that if we have small number of relays in the network, the probability of selecting incorrect relay combination is also small for Q-learning using independent channel model.

Fig. 3.8 shows the throughput performance using Jake's fading model compared with the independent channel case using Q-learning based ϵ greedy mechanism when a network has larger number of relays. In both cases, it is observed that our proposed selection performs well when the time variation in the fading model are utilized. This implies that when a network has larger number of relays, the probability of selecting a incorrect relay combination is higher for the system under independent channel realizations. On the other-hand, the Q-learning algorithm utilizes the memory introduced in the time-varying channel to learn about the channel and using learning process the destination takes proper

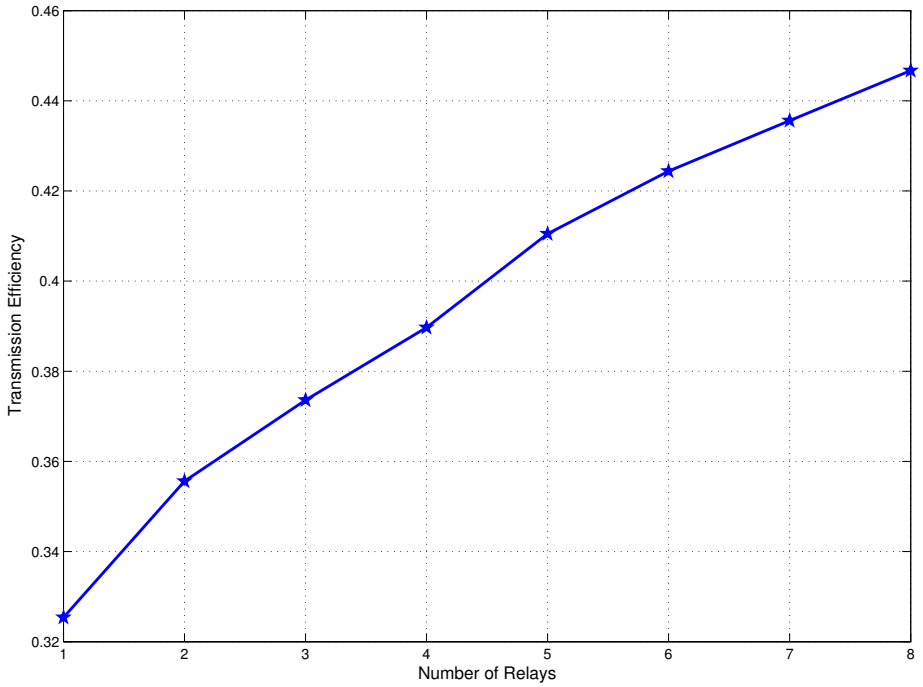


Figure 3.9: Transmission efficiency vs number of relays where Q-learning using ϵ greedy mechanism is used, and Jake's channel model is also used where $V = 5km/h$.γ_{s-r} =20dB and γ_{r-d} =8dB

decision based on previous relay selection experience.

Fig. 3.9 shows the throughput performance as a function of number of relays in the network. These results are based on fixed SNR from relays to the destination. However, from the source to relay the SNR is fixed to 20dB. Results show that as we increase the number of relays in the network, the throughput performance is improved. This is due to the fact that, the large number of relays in the network allows more links from the relay nodes to the destination. As a result, once the exploration is completed, the destination has a large number of combination to find the proper combination from the Q-learning table to maximize the throughput.

Algorithm 2 Effect of exploration to exploitation ratio on Q-learning relay selection algorithm

integer = x_n
for (initial time to end time) **do**
  if *counter* == 0 or first packet **then**
    Choose source and relay combination where all reliable relays are present
  else
    Choose source and relay combination associated with the highest Q-value in the Q-table
    $counter = counter + 1$
  end if
  if $counter \geq x_n$ **then**
    $counter = 0$
  end if
  Update Q-table using (3.19)
end for

3.5.2 Effect of Exploration to Exploitation Ratio (EER) on Q-learning Relay Selection

In this subsection, our algorithm operates in such a way that the destination chooses the exploitation mode more than the exploration mode where the destination adopts the Q-learning algorithm for relay combination selection. In this case, the destination operates in the exploration mode after certain fixed number of packets. Otherwise, the destination operates in the exploitation mode for relay combination selection using the Q-learning table. In our simulations, we noted that the exploration mode helps the destination to make proper decisions on future relay selection. However, operating in the exploration mode is known to be expensive since in this case all reliable relays participate in retransmissions as our system employs TDMA for relay communications. Algorithm 2 summarizes this source and relay combination selection protocol.

Tables 3.3–3.5 show the transmission efficiency for different exploration to exploitation ratios when $V = 5km/h$, $30km/h$, and $100km/h$. We set the SNR from source to relay link $\gamma_{s-r} = 20$dB and all other links are set at 8dB. From the results, we can see that for all three cases, the transmission efficiency changes with the change of exploration to

Table 3.3: Transmission efficiency for different exploration to exploitation ratio. $V = 5km/h$. $\gamma_{r-d} = 8$dB

Exploration to Exploitation ratio	Transmission Efficiency ($V = 5km/h$)
1/100	0.3600
1/1000	0.3632
1/2000	0.3756
1/3000	0.3898
1/4000	0.3943
1/5000	0.4077
1/6000	0.4549
1/7000	0.4652
1/7100	0.4907
1/7200	0.4421
1/7900	0.3877
1/8000	0.3607

Table 3.4: Transmission efficiency for different exploration to exploitation ratio. $V = 30km/h$. $\gamma_{r-d} = 8$dB

Exploration to Exploitation ratio	Transmission Efficiency ($V = 30km/h$)
1/100	0.3612
1/1000	0.3804
1/2000	0.3979
1/3000	0.4297
1/4000	0.4260
1/5000	0.4424
1/6000	0.4549
1/7000	0.4952
1/7100	0.5009
1/7200	0.4890
1/8000	0.4726
1/8500	0.3986

Table 3.5: Transmission efficiency for different exploration to exploitation ratio. $V = 100km/h$. $\gamma_{r-d} = 8$dB

Exploration to Exploitation ratio	Transmission Efficiency ($V = 100km/h$)
1/100	0.3964
1/1000	0.4629
1/2000	0.4805
1/3000	0.4998
1/4000	0.4668
1/5000	0.4659
1/6000	0.4547
1/7000	0.3759

exploitation ratio (EER). It can be noted that, EER 1/7100 provides the maximum transmission efficiency for both cases, when $V = 5km/h$ and $V = 30km/h$. Similarly, when $V = 100km/h$ EER 1/3000 provides maximum transmission efficiency. It can also be noted that for $V = 100km/h$ exploration to exploitation ratio increased because channel changes very fast compared to other two cases when $V = 5km/h$ and $30km/h$.

Figs. 3.10–3.12 show the transmission efficiency comparison between the system in [9], the effect of exploration-to-exploitation ratio on the Q-learning and the effect of ϵ greedy mechanism on Q-learning. From the results, one can see that in all three cases, the EER outperforms the Q-learning using ϵ greedy mechanism and the system in [9]. This implies that exploration is more expensive than exploitation in TDMA communication mode, as in exploration all reliable relays participate to forward the source information to the destination.

Fig. 3.13 shows the effect of exploration-to-exploitation ratio on the Q-learning relay selection algorithm when the channels are modeled using Jake's Rayleigh fading model with $V = 5km/h$, $30km/h$, and $100km/h$ and the case of independent fading realizations. As the results show, our Q-learning algorithm utilizes the memory introduced in the time-varying channel to learn about the different channels, and uses this learning process to improve the relay selection procedure as time elapses.

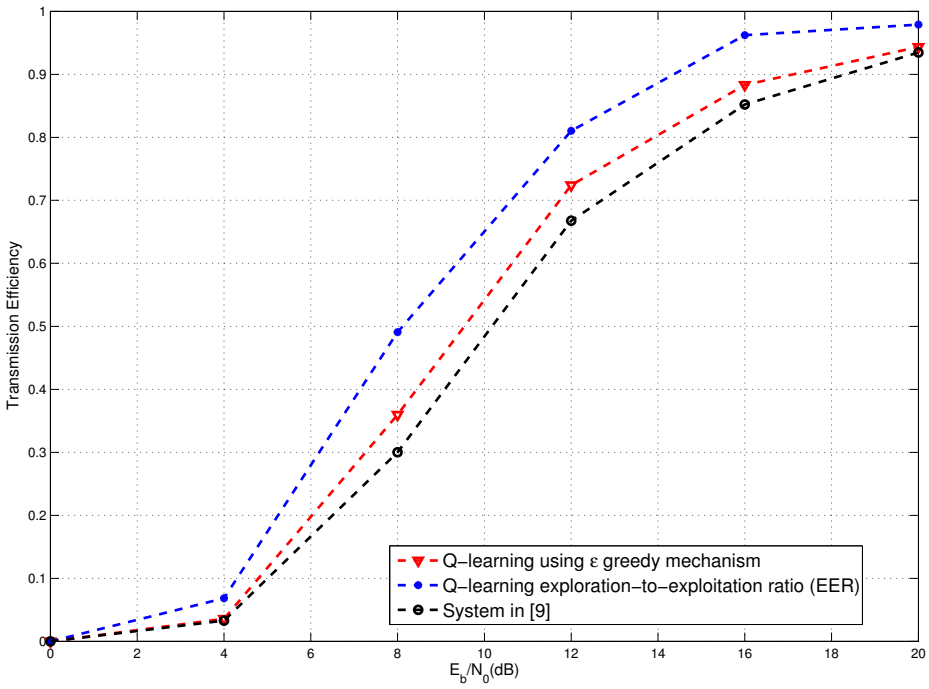


Figure 3.10: Transmission efficiency comparison of the system in [9], Q-learning using ϵ greedy mechanism and the effect of exploration-to-exploitation ratio on the Q-learning considering Jake's model with $V = 5km/h$ andγ_{s-r} =20dB.

Fig. 3.14 shows the percentage usage of relay combination for the system in [9] and the effect of the exploration-to-exploitation ratio on the Q-learning algorithm. As evident from these results, the percentage of relay usage for the system [9] is always four regardless of the link quality given by the SNRs. This is expected as the system in [9] is based on fixed number of relays. However, the number of transmitting relays varies for our Q-learning based cross-layer approach as it maximizes the link-layer transmission efficiency. In other-wards, Fig. 3.14 indicates the percentages of usage of relays that maximizes the transmission efficiency. From the results, one can see that at low SNRs, small number of relays are employed as the channels between relays to the destination are poor. As the SNR increases, channels become more reliable and more relays are used in retransmission. Also one should note that as the node speed goes high, the Q-learning acts on the limited memory of the channel and hence, more relays are employed relative to the case with lower node speeds.

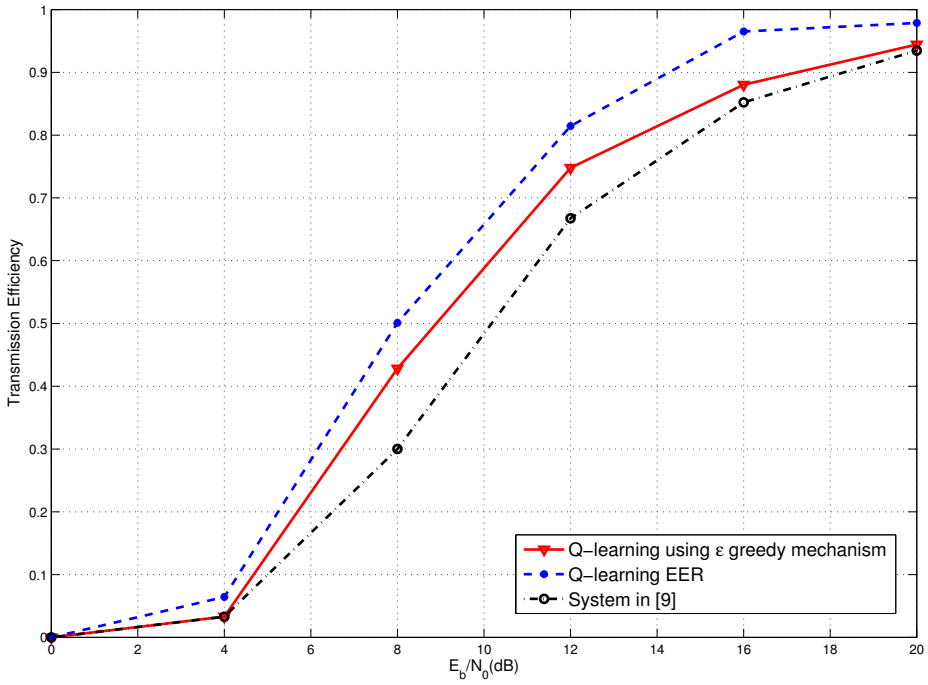


Figure 3.11: Transmission efficiency comparison of the system in [9], Q-learning using ϵ greedy mechanism and the effect of exploration-to-exploitation ratio on the Q-learning considering Jake's model with $V = 30km/h$ andγ_{s-r} =20dB.

Figure 3.15 shows the transmission efficiency comparison for different SNR values from the source to the relay link. The results clearly show that, as SNR decreases for the link between the source and the destination, the transmission efficiency is also decreased. This is due to the fact that, when the SNR on the relay to destination is low, the relays will have more errors. As a results, a smaller number of links are available between the relays and destination.

Figure 3.16 shows the usage of reliable relay combinations for different SNR values from the source to the relay links. We can see that at $\gamma_{s-r} = 5$dB there is no instance where four relay combinations are used. The reason behind this is due to the low SNR=5dB, where no four relays will be used for retransmission during exploration phase. As we mentioned before exploration phase is used to fill all entries in the Q-table when all relays correctly decode the source's message. Therefore, when the S-R link is poor, not all relays are used in exploration.

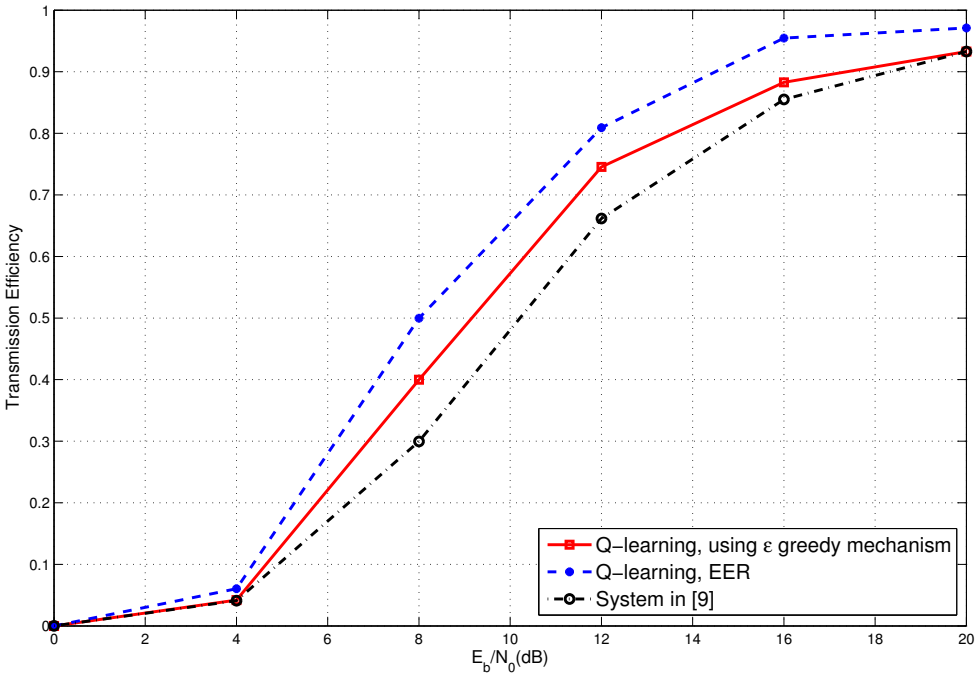


Figure 3.12: Transmission efficiency comparison of the system in [9], Q-learning using ϵ greedy mechanism and the effect of exploration-to-exploitation ratio on the Q-learning considering Jake's model with $V = 100km/h$ andγ_{s-r} =20dB.

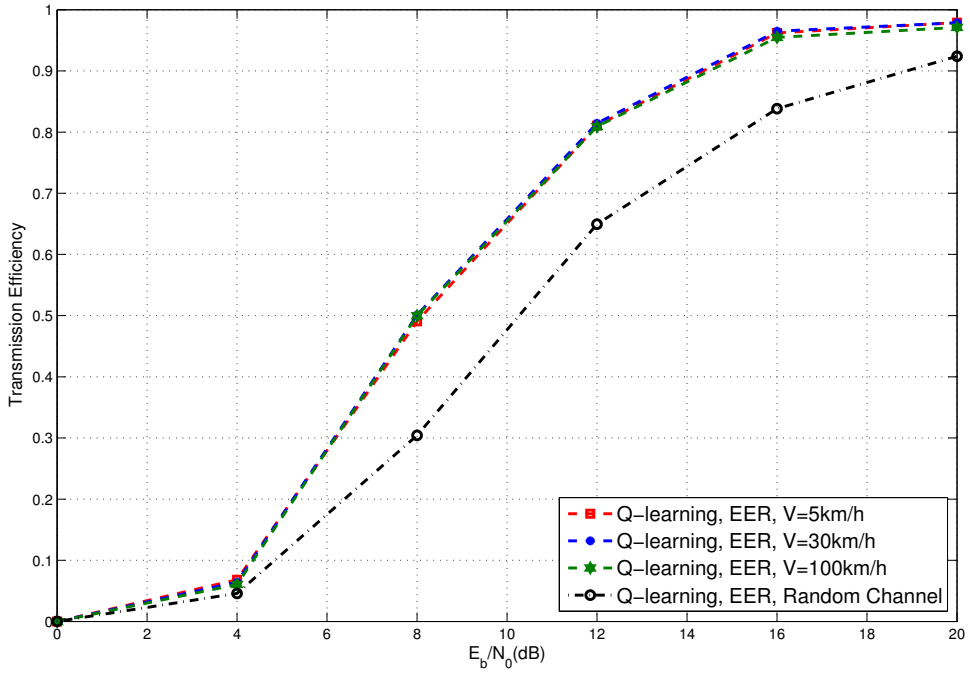


Figure 3.13: Effect of exploration-to-exploitation ratio with node speed $V = 5km/h$, $V = 30km/h$, $V = 100km/h$ and independent fading model with γ_{s-r} =20dB.

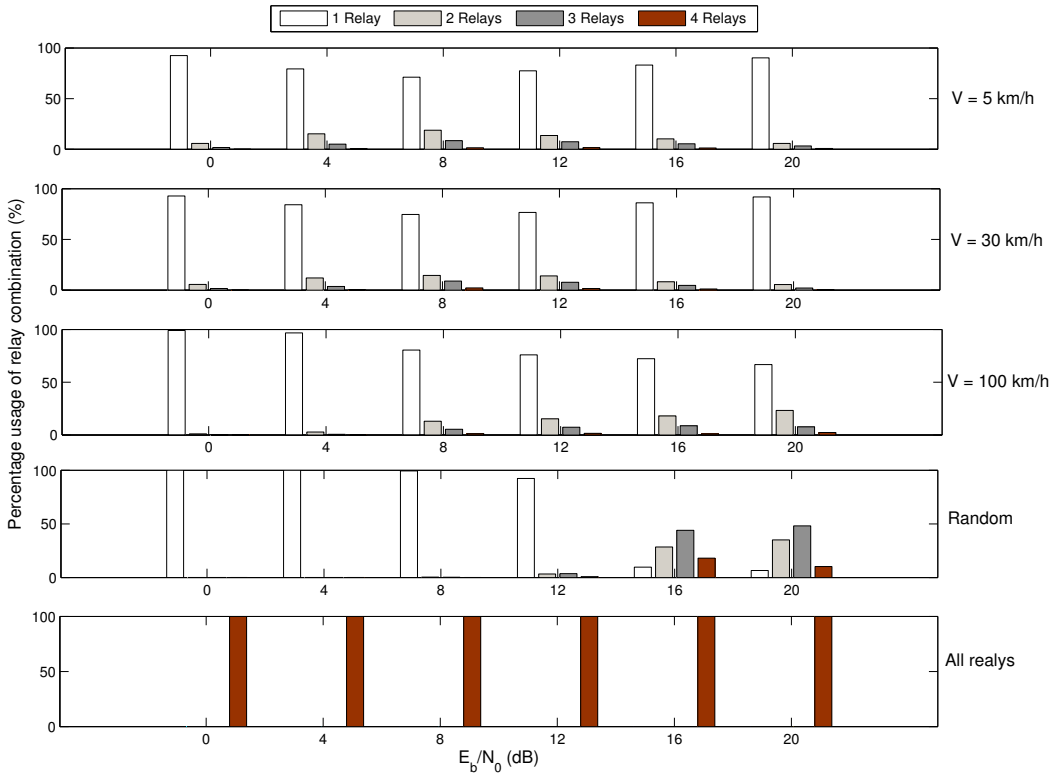


Figure 3.14: Usage of reliable relay combination for system in [9], effect of exploration to exploitation ratio on Q-learning when channels are Jake's Rayleigh fading channel with $V = 5km/h$, $V = 30km/h$, $V = 100km/h$ and effect of exploration to exploitation ratio on Q-learning when channels are random.$\gamma_{s-r} = 20$dB.

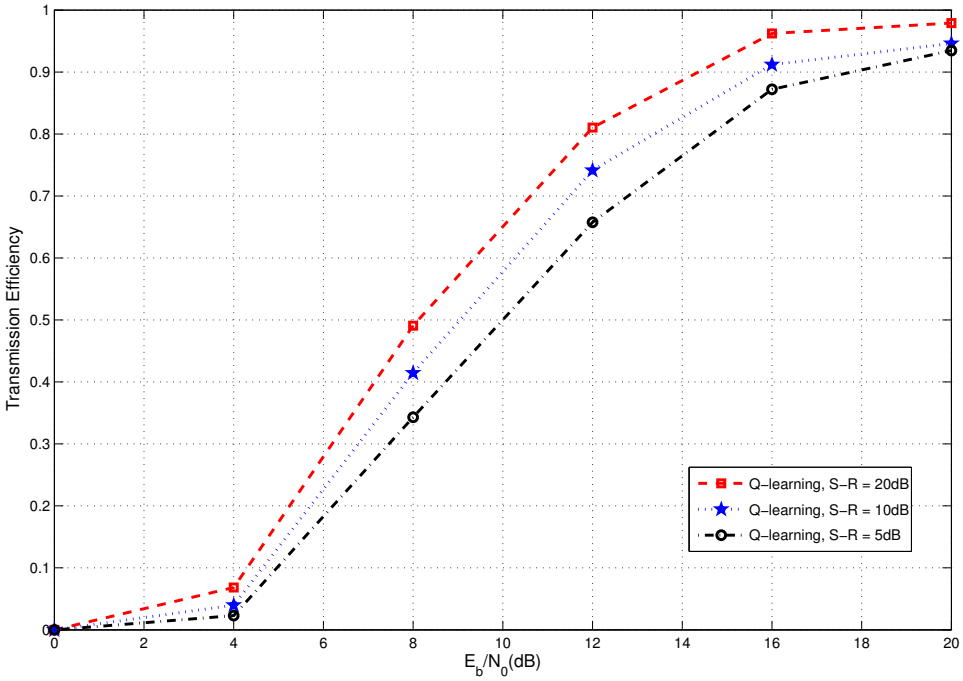


Figure 3.15: Transmission efficiency comparison for different SNR values of S-R link. Where, jake's model is used as fading channel, $V = 5km/h$.

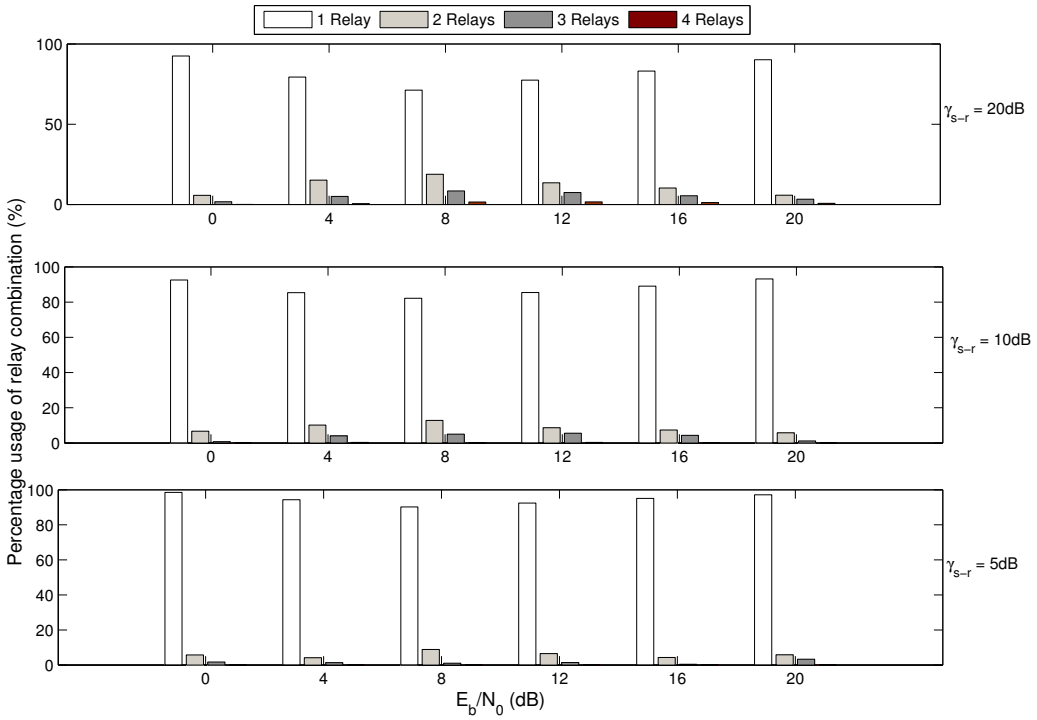


Figure 3.16: Usage of reliable relay combination for different SNR values of S-R link. Where, Jake's model is used as fading channel, $V = 5km/h$.

3.6 Conclusions

In this chapter, we have presented Q-learning based cross-layer relay selection scheme to maximize the link layer transmission efficiency. The proposed learning algorithm utilizes the memory introduced by the time-varying Rayleigh fading channel to learn and act on future relay selections. Hence improved throughput maximization relative to the conventional schemes with no learning involved. We have examined that the ϵ greedy mechanism and the effect of exploration-to-exploitation ratio on the Q-learning provide transmission efficiency gain over existing systems where all reliable relays participate in retransmission. Moreover, our proposed system utilizes the channel resources more efficiently than existing systems. Hence the system uses the bandwidth more efficiently and also provides improved transmission efficiency.

Chapter 4

Learning Based Transmit Antenna Selection of Multiple-Antenna Relays

In the previous chapter, we have considered all relays operating with a single transmit antenna and determined the transmission efficiency. To meet the increasing demand for high data rate services, transmit antenna diversity has been widely embraced as effective method to enhance the capacity of wireless systems, while operating on the same bandwidth compared to the single antenna case. In this chapter, we extend our study of chapter 3 to design relay networks with multiple antennas over Rayleigh fading channels.

4.1 Introduction

MIMO technology can potentially improve network throughput and transmission reliability by utilizing multiple antennas at the transmitter and/or at the receiver. Now it has been widely used in many standards [40]–[42] due to its ability to significant performance enhancement of wireless communication systems [43], [44]. In this technology, multiplexing techniques take advantage of the rich scattering environment to increase transmission capacity [45] and diversity combats fading to enhance the transmission reliability [46], [47].

In the previous chapter, all relays in the system are assumed to be equipped with a single antenna. This precludes the beneficial use of MIMO technology in conjunction with relaying systems. However, it has been theoretically shown that the performance of relaying systems can be significantly enhanced by exploiting the benefits offered by MIMO technology [48]. In [48] the author investigated ergodic capacity of dual-hop AF MIMO system. The work in [49] shows the effect of multiple antennas on outage probability in relay networks.

In multiple antenna environment, selecting all antennas is not an optimal solution as cost increases with the number of RF chains needed for multiple antennas. A MIMO system with antenna selection can improve the performance compared to the case with no antenna selection. However, the computational load and extra memory are required for an optimal selection through an exhaustive search over all possible antenna subsets [50], [51]. This load grows exponentially with the increase of total number of available antennas. To address this issue, antennas can be selected by machine learning techniques using past antenna selection experience. In [52], machine learning is used for channel selection in cognitive ad-hoc Single-Input and Single-Output (SISO) networks. Machine learning is also used in [53] to address the channel allocation problem for heterogenous cognitive networks. Similar to previous chapter, the Q-learning algorithm can also be implemented in antenna selection for the relay nodes. In [54], co-operative Q-learning is used to assign channels for cognitive nodes. Q-learning is also used in [55] to assign channels for two cognitive nodes from a set of two channels. On the other hand, in [56] the authors evaluated the performance of user satisfaction based Q-learning channel selection algorithm for ad-hoc networks where cognitive nodes in heterogeneous environments are considered.

Motivated by the works in [9], [49], [50], [51], we propose a cross-layer antenna selection scheme from the reliable relays using Q-learning that maximize the link layer throughput. Another advantage of the proposed scheme is due to the average antenna

utilization of reliable relays to ensure efficient use of available bandwidth. From the above, this chapter is organized as follows. Section 4.2, describes the system model for multiple-antennas relay networks. Performance analysis is presented in section 4.3. Simulation settings and results of the proposed algorithm are presented in Section 4.5. Finally, conclusions are drawn in Section 4.6.

4.2 System Model

Similar to chapter 3, here we also consider a cooperative diversity network consisting of a source, a destination and N relays as shown in Fig. 4.1. In this scheme, source node transmits a packet to the destination node with cyclic redundancy check (CRC) bits appended to its message for error detection. All relay nodes overhear the transmission due to the broadcast nature of the channel. After receiving a packet, the destination and relays decode the source's message and check for errors. If the destination correctly decodes the source's message, then it sends a positive acknowledgment (ACK) to the source and relays, through a error free feedback channel which is assumed to be perfect. Otherwise, the destination sends negative acknowledgment (NACK) and A_SEL (antenna select) packet, requesting for retransmission. When a positive ACK packet is received, the source transmits a new packet and all relays remain silent. But when NACK and A_SEL are received, all selected antenna associated with reliable relay(s) forward source information to the destination. Figs. 3.2 and 3.3 show the time diagram and the complete flow chart of the system. Finally the destination decodes the combined signal from source and relay(s) nodes.

This retransmission process continues until the destination correctly decodes the source's message or the number of retransmission reaches its maximum N_{max}. We assume source and destination are equipped with single antenna. But the relays are equipped with one receive antenna and N_T transmit antennas. All packets are sent through TDMA

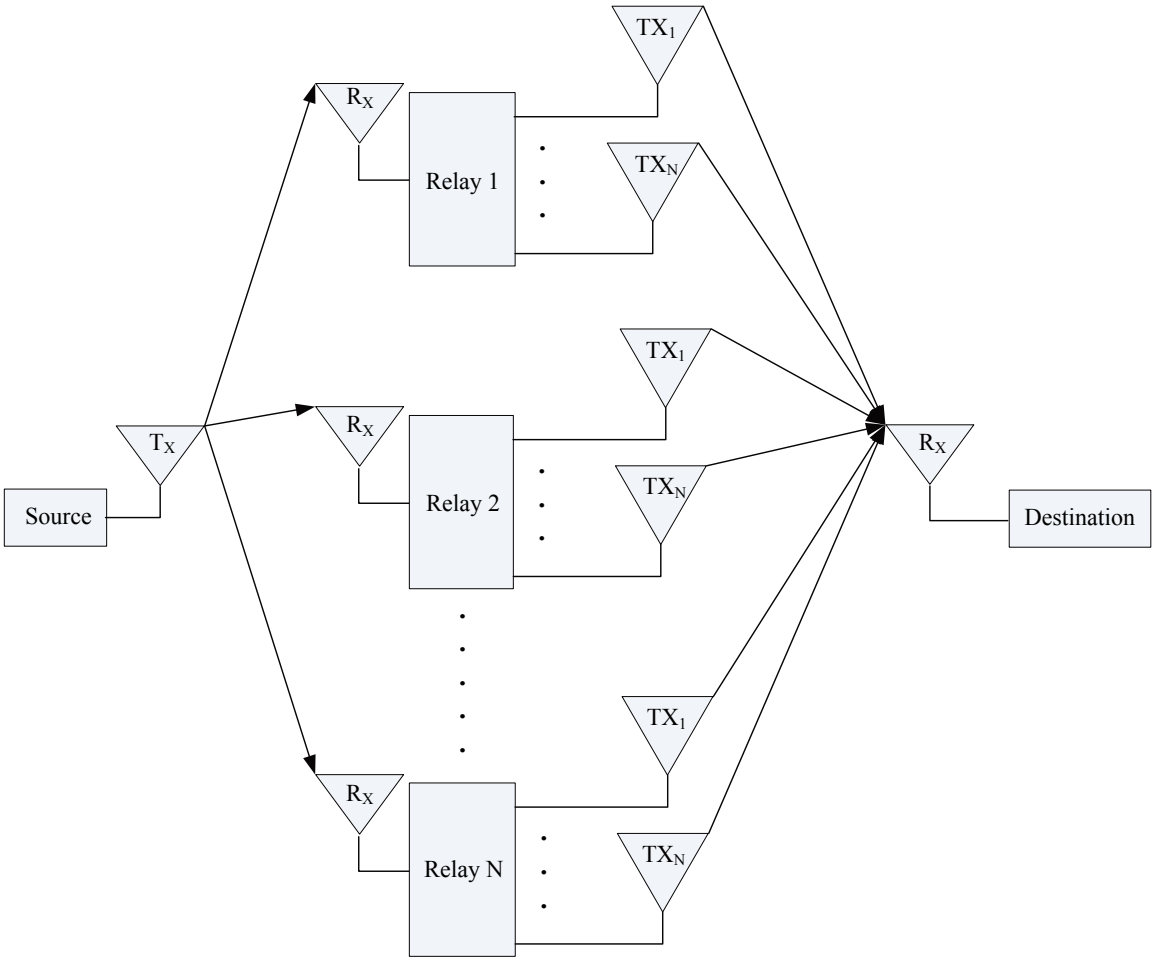


Figure 4.1: Schematic illustration of the system under consideration.

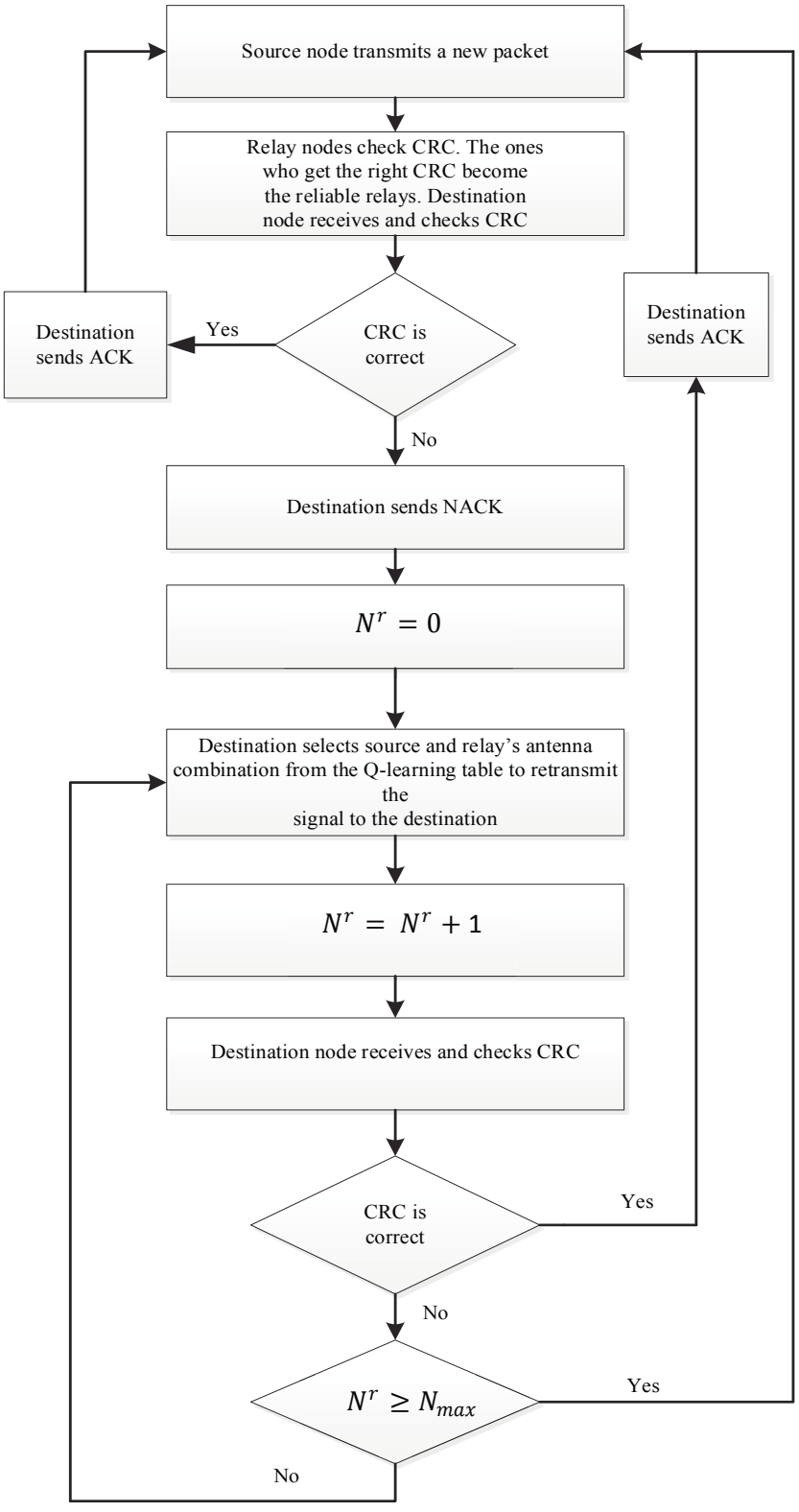


Figure 4.2: Flow chart of the proposed system.

communication mode over multipath time-varying Rayleigh fading channel modeled using Jake's model. We use this model to take better decision on Q-learning based antenna selection algorithm from the reliable relays. This algorithm selects the best source and relay combination to maximize transmission efficiency using ϵ greedy mechanism presented in [39] and also examines the effect of exploration to exploitation ratio. For simplicity, we also assumed channels are fixed for the entire duration of a packet transmission.

Complex channel coefficient of source to destination (S-D), source to relay (S-R), and relay to destination (R-D) are denoted as h_{sd}, h_{sr}, and H_r respectively which is modeled as complex Gaussian distribution with zero mean and unit variance. The received signal from source to relay and source to destination are defined as y_{sd} and y_{sr} respectively, which has been shown in (3.1) and (3.2). We also express the received signal from relay to destination $\underline{\mathbf{Y_{rd}}}$, which is $((N_T \times N) \times 1)$ vector.

$$\underline{\mathbf{Y_{rd}}} = \sqrt{E_r}\underline{\mathbf{H_{rd}}}\hat{x} + \underline{\mathbf{n_{rd}}}, \tag{4.1}$$

where $\hat{x}$ is the estimated symbol at the relay. E_r denote the transmitted energy from relay respectively, additive noise n_{rd} is defined as Gaussian random variables with zero mean and variance σ^2. $\underline{\mathbf{H_{rd}}}$ and $\underline{\mathbf{n_{rd}}}$ are the $((N_T \times N) \times 1)$ vector and can be defined as

$$\underline{\mathbf{Y_{rd}}}^\top = \begin{bmatrix} Y_1^1 & Y_1^2 & ..... & Y_1^{N_T} & ..... & Y_N^1 & Y_N^2 & ..... & Y_N^{N_T} \end{bmatrix}, \tag{4.2}$$

$$\underline{\mathbf{H_{rd}}}^\top = \begin{bmatrix} H_1^1 & H_1^2 & ..... & H_1^{N_T} & ..... & H_N^1 & H_N^2 & ..... & H_N^{N_T} \end{bmatrix}, \tag{4.3}$$

$$\underline{\mathbf{n_{rd}}}^\top = \begin{bmatrix} n_1^1 & n_1^2 & ..... & n_1^{N_T} & ..... & n_N^1 & n_N^2 & ..... & n_N^{N_T} \end{bmatrix} \tag{4.4}$$

where H_1^1 is the channel between first antenna of relay one and the destination. Similarly, H_2^1 is the channel between first antenna of relay two and the destination and so on. Similar to previous chapter, here we also use non-coherent Difference Binary Phase Shift Keying (DBPSK) to overcome the problem of channel estimation at the receiver side and hence

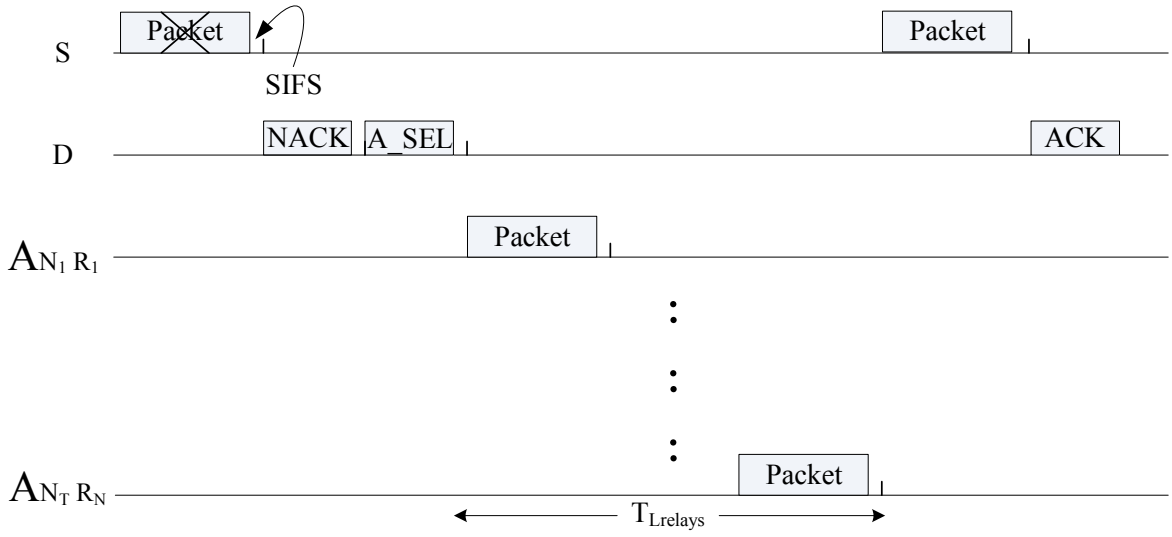


Figure 4.3: Antenna selection timing diagram

lower complexity. It also reduces the communication overhead and wasted power as in pilot and training based channel estimation techniques, specially when fading is rapid. To avoid CSI estimation, here we also employ selection combining (SC) technique to combine the signals from source and relays.

4.3 Performance Analysis

In this section, we analyze the transmission efficiency (i.e. normalized throughput) at the destination. The transmission efficiency for adaptive DF by considering packet transmission time from relay's transmit antennas to destination can be written as

$$\eta = \frac{(T_L - T_C)P_s k}{T_L E(T_{packet}) + E(T_{Lantennas})}, \tag{4.5}$$

where T_L and T_C are the transmission time of data packet and CRC bits, respectively. Packet successful probability and average number of transmission per packet are given by

P_s and $E(T_{packet})$, respectively. k is number of bits per symbol and $E(T_{Lantennas})$ is the average packet transmission time from the relay's antennas to the destination per packet. Now, the packet successful probability P_s is given by [9],

$$P_s = \sum_{i=0}^{N} \left(1 - PER_{sd} \left(PER_{RetxAntenna}(i)\right)^{N_{max}}\right) P_r(i), \tag{4.6}$$

where N is the total number of relays, $PER_{RetxAntenna}(i)$ denote the average PER of the i^{th} reliable relay retransmission given by

$$PER_{RetxAntenna}(i) = 1 - \left(1 - SER_{RetxAntenna}(i)\right)^{\frac{L_p}{k}} \tag{4.7}$$

$SER_{RetxAntenna}$ is average SER of retransmission and L_p is total packet length. When not a single relay could decode the source signal correctly, which is the case when $i = 0$, the average $PER_{RetxAntenna}(0) = 1 - \left(1 - SER_{RetxAntenna}(0)\right)^{\frac{L}{k}}$ and $SER_{RetxAntenna}\,(0) = SER_{sd}$. $P_r(i)$ is the probability that i relays correctly decode the source message has been shown in (3.13)

The average number of transmission time per packet $E(T_{packet})$ and is given by

$$E(T_{packet}) = \sum_{i=0}^{N} V_{packet}(i) P_r(i), \tag{4.8}$$

$$V_{packet}(i) = 1 - PER_{sd} + PER_{sd}\Bigg[\sum_{j=2}^{N_{max}} j\left(PER_{RetxAntenna}(i)\right)^{j-2} \left(1 - PER_{RetxAntenna}(i)\right)\left(1 + N_{max}\right)\left(PER_{RetxAntenna}(i)\right)^{N_{max}-1}\Bigg]. \tag{4.9}$$

Similarly, $E(T_{Lantennas})$ is the average packet retransmission time for a packet sent the

destination, and is given by

$$E(T_{Lantennas}) = N_T \sum_{i=0}^{N} iV_{Lantennas}(i)P_r(i), \tag{4.10}$$

$$V_{Lantennas}(i) = T_{Lantennas} PER_{sd} \Bigg[\sum_{j=2}^{N_{max}} j(PER_{RetxAntenna}(i))^{j-2} \\ (1 - PER_{RetxAntenna}(i))\,(1 + N_{max})\,(PER_{RetxAntenna}(i))^{N_{max}-1} \Bigg]. \tag{4.11}$$

where N_T is number of transmit antennas per relay and $T_{Lantennas}$ is the packet transmission time from an antenna. In next subsection, we present our proposed Q-learning algorithm to select transmit antenna from the reliable relays to improve the transmission efficiency.

4.4 Transmit Antenna Selection Using Q-learning

Similar to previous chapter, the destination also adopts Q-learning algorithm. In this algorithm, the destination should learn to choose the best action after a set of trail and error to maximize the total reward when channels are modeled as time-varying Rayleigh fading. For our system, an action is defined as packet transmission process through possible source and selected reliable relay's transmit antenna(s) combination and the reward is defined as the transmission efficiency for a selected action. In the Q-learning algorithm, destination selects an action by exploration or exploitation. Here the main goal is also finding a balance between exploration and exploitation.

In exploration mode of the Q-learning, the destination selects a combination where all reliable relay's transmit antenna are present so that destination can update all possible source and relay's transmit antenna combinations. It can be noted that, all relay's transmit antenna access the channel using the channel using TDMA mode to forward the

Table 4.1: Q-learning Table For Transmit Antenna Selection

$Time$	$Q(SA_{1R_1})$	$Q(SA_{2R_1})$	..	$Q(SA_{N_TR_1})$	$Q(SA_{1R_2})$	..	$Q(SA_{1R_1}A_{2R_2}...A_{N_TR_N})$
0	0	0	..	0	0	..	0
..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..
t_1	$Q_{t_1}(SA_{1R_1})$	$Q_{t_1}(SA_{2R_1})$	..	$Q_{t_1}(SA_{N_TR_1})$	$Q_{t_1}(SA_{1R_2})$	..	$Q_{t_1}(SA_{1R_1}A_{2R_2}...A_{N_TR_N})$
t_1+1	$Q_{t_1+1}(SA_{1R_1})$	$Q_{t_1+1}(SA_{2R_1})$	..	$Q_{t_1+1}(SA_{N_TR_1})$	$Q_{t_1+1}(SA_{1R_2})$	..	$Q_{t_1+1}(SA_{1R_1}A_{2R_2}...A_{N_TR_N})$

source message to the destination. But in the exploitation mode, the destination selects an action that has maximum Q-value in the Q-learning table.

Q-table is used at the destination to store and update the Q-value for different combination of source and reliable relay's transmit antenna(s). A single element subset w_a is chosen from set W_a can be written as

$$W_a = \{\{SA_{1R_1}\}, \{SA_{2R_1}\}, ..., \{SA_{N_TR_N}\}, ..., \{SA_{1R_1}A_{2R_2}...A_{N_TR_N}\}\}, \tag{4.12}$$

For example, SA_{1R_1} is defined as a single element subset of W_a when only source(S) and antenna one of relay one (A_{1R_1}) are used for packet transmission. SA_{2R_1} is used when only source(S) and antenna two of relay one (A_{1R_1}) are used for packet transmission. Similarly, $SA_{1R_1}A_{2R_2}...A_{N_TR_N}$ is defined as another single element subset of W_a when all antennas of all the relays are used for retransmission. Now, we define a as an action for which destination gets a reward r_a. Reward can be calculated from (4.5) and the Q-value $Q_t(a)$ is estimated after an action a at time t. The Q-values are updated according to the function has been shown in 3.19. Initially we set all values of the Q-table to zero. After that, the destination chooses an action by exploration or exploitation. For the selected action destination gets a reward ($r_a \geq 0$) then it calculate it's Q-value to update the Q-table.

Table 4.1 shows the Q-table where we can see that all Q-values are initialized to

zero at time zero. For instance, we assume that at time $t_1 + 1$ single element subset $SA_{N_T R_N}$ is selected by exploitation because Q-value of single element subset $SA_{N_T R_N}$ has maximum Q-value among all in the Q-table at time t_1. In table 4.1, $Q_{t_1+1}(SA_{N_T R_1})$ and $Q_{t_1}(SA_{N_T R_1})$ represent the Q-value at time $t_1 + 1$ and t respectively. So at time $t_1 + 1$ $Q_{t_1}(SA_{N_T R_1})$ is updated by $Q_{t_1+1}(SA_{N_T R_1})$ and other Q-values remain unchanged. Similarly, if $Q_{t_1}(SA_{1R_1} A_{2R_2} ... A_{N_T R_N})$ is selected by exploitation at time t_1 then, $Q_{t_1}(SA_{1R_1} A_{2R_2}$ $... A_{N_T R_N})$ is updated by $Q_{t_1+1}(SA_{1R_1} A_{2R_2} ... A_{N_T R_N})$ at time $t_1 + 1$ and in this case the destination also updates all possible single antenna subsets case by the estimate of Q-value at time $t_1 + 1$. Here, we update using only single antenna case because in SC combining techniques, the highest SNR link is selected for decoding. So if the destination uses the SC combining techniques then updating by estimation for multiple antenna subsets will not outperform the single antenna case in terms of Q-value. In this process, destination does not need CSI information for relay antenna selection. That is no overhead incurred by the system where all reliable relays do not need to send extra bits to estimate the CSI for relay's transmit antenna selection.

4.5 Simulation Results

In this section, we present simulation results to assess the performance of the adaptive DF cooperative system when relay nodes have multiple transmit antennas and source and destination with only one antenna. We examine the transmission efficiency and usage of relay combination under different time-varying Rayleigh fading channels. The simulation parameters are as follows, packet transmission time and CRC bits transmission time are $T_L = 2.667 \times 10^{-4}$s and $T_C = 4.167 \times 10^{-6}$s respectively. Please note that packet length is 1024 bits, CRC is 16 bits long and data rate is $3.84 \times 10^6 bps$. The maximum number of retransmissions $N_{max} = 3$ and unless otherwise specified the total available relays is N= 4 and average SNR between source to relay(s) link as $\gamma_{s-r} = 20$dB. .

4.5.1 Q-learning Based Antenna Selection Using ϵ Greedy Mechanism

In this subsection, Q-learning algorithm selects a source and antenna(s) combination from the reliable relays based on ϵ greedy mechanism presented in [39]. In this mechanism, the destination chooses exploration with probability ϵ and selects an action that has maximum Q-value in Q-learning table (Q-table) with probability $(1-\epsilon)$. The Destination starts the exploration with a very high ϵ value and updates ϵ after each successful packet transmission as in (4.13),

$$\epsilon = \epsilon - \frac{\epsilon}{m_a}. \tag{4.13}$$

where m_a is the update parameter. From (4.13), we can write the probability of selecting a source and antenna(s) combination as

$$z_j = \begin{cases} 1 - \dfrac{\epsilon}{m_a}, & \text{if the action is exploitation} \\ \dfrac{\epsilon}{m_a}, & \text{otherwise} \end{cases} \tag{4.14}$$

In our simulation, we set the update parameter m_r in such a way that the destination chooses exploration frequently. It is to be noted that, exploration helps the destination to make good decision on antenna(s) selection. Algorithm 3 summarizes this source and antenna(s) combination selection protocol.

By setting $m_a = m_r$ a cooperative relay network is simulated over a time-varying Rayleigh fading channels modeled using Jake's Rayleigh fading model. In Fig.4.4 the throughput performance of relay with single transmit antenna case is compared with the relay with two transmit antennas case. In two transmit antenna case, the destination uses Q-learning based ϵ greedy mechanism to select relay but both transmit antennas are used to forward source message to the destination. In other-words, no transmit antenna selection algorithm is employed for the relays to forward the source message to the des-

Algorithm 3 Q-learning algorithm for antenna selection using ϵ greedy mechanism

ϵ = Probability of choosing exploration
rv = Uniformly distributed [0,1]
for (initial time to end time) **do**
    $\epsilon = \epsilon$/update parameter
    $p = \epsilon$
    if $p < rv$ or $\epsilon ==$ initial value **then**
        Choose source and antenna(s) combination where all reliable relay's transmit antennas are present
    else
        Choose source and antenna(s) combination associated with the highest Q-value in the Q-table
    end if
    if $\epsilon > 1$ **then**
        ϵ to initial value
    end if
    Update Q-table using (3.19)
end for

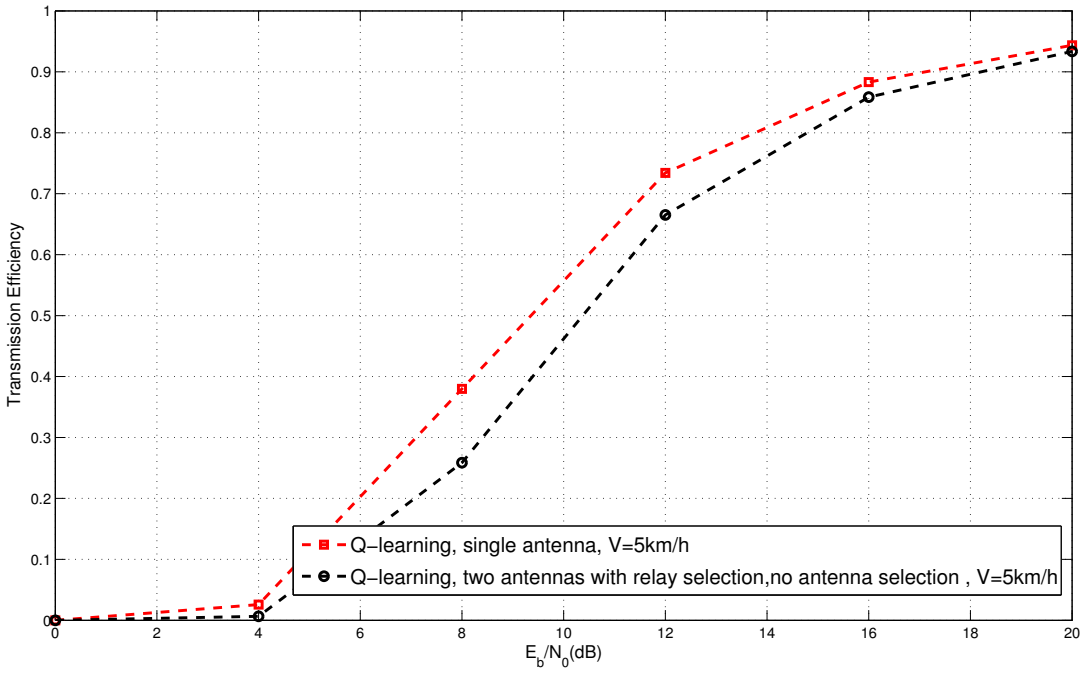


Figure 4.4: Transmission efficiency comparison between the Q-learning algorithm using ϵ greedy mechanism, when relays are equipped with one transmit antenna and also when relays are equipped with two transmit antenna but no antenna selection is used under Jake's channel model, where $V = 5km/h$ and γ_{s-r} =20dB.

tination. From the results, we can see that single transmit antenna case outperform the two transmit antennas case since no transmit antenna selection algorithm is employed. As noted before work in [50, 51] showed that selecting all antenna is not the optimal solution for the performance enhancement. To address this issue transmit antenna selection using Q-learning could be a solution to improve the system performance.

By adding the Q-learning relay selection algorithm, Fig. 4.5 compares the throughput performance of the cooperative relay network for the case with and without transmit antenna selection when relays are equipped with two transmit antennas over time-varying Rayleigh fading environment. Results show that antenna selection using the Q-learning provides significant throughput gain over the no antenna selection case. These results also suggest that, in presence of selection algorithm full diversity gain can be realized at the destination to minimize bit error rate and maximize transmission efficiency.

Fig. 4.6 shows the throughput performance of the cooperative relay network for various number of transmit antennas. Results show that, throughput is increased as we increase the number of transmit antennas for the relay nodes. This implies that for larger number of available channels between the relay nodes, the Q-learning algorithm utilizes the memory introduced in the time-varying channels to learn about the different channel and the learning process helps destination to choose the proper antenna subset to maximize the throughput.

Fig. 4.7 shows the throughput performance as a function of number of relays in the network. These results are based on γ_{s-r} =20dB and all other links are fixed to γ_{r-d} =8dB. From the results, we can see that two antenna case always outperform the single antenna case as more reliable links between the relays to the destination are available. More reliable links help the destination to take proper decision on antenna selection. It can be observed that, the transmission efficiency of one relay equipped with two antennas case is identical with two relays equipped with one antenna case and this trend continues for other similar cases.

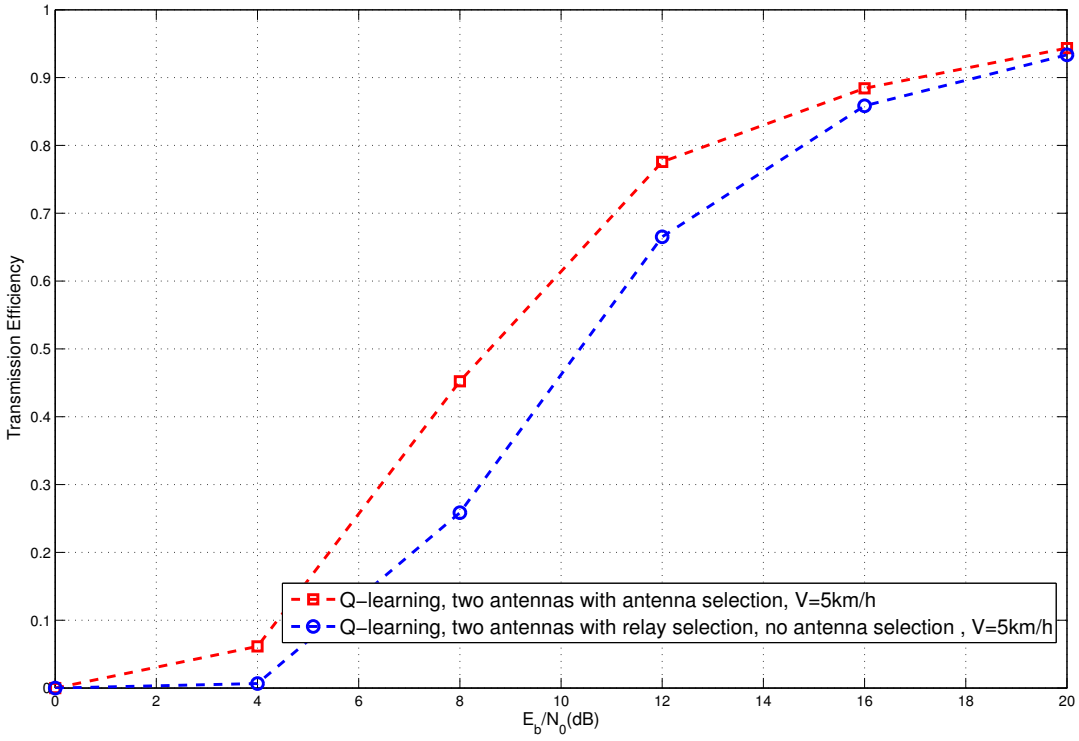


Figure 4.5: Transmission efficiency comparison of system under Q-learning algorithm using ϵ greedy mechanism, with and without transmit antenna selection, when relays are equipped with two transmit antennas and Jake's channel model is used, where $V = 5km/h$ and γ_{s-r} =20dB.

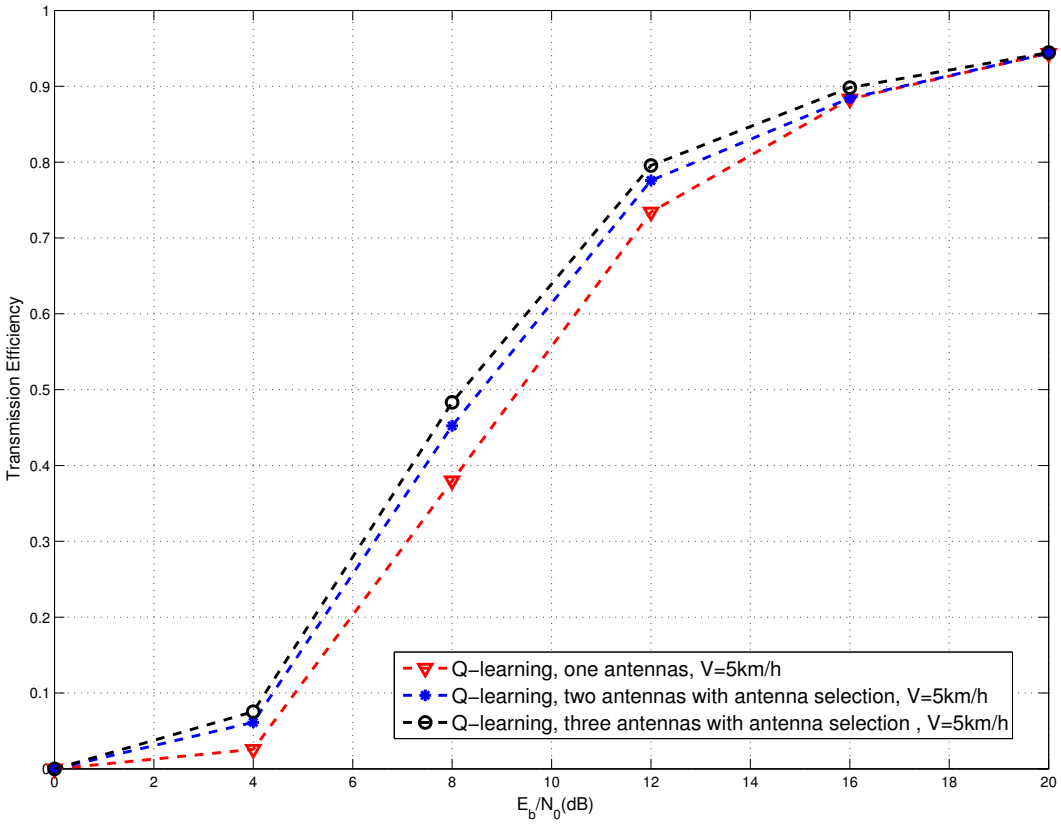


Figure 4.6: Transmission efficiency comparison of system under Q-learning algorithm using ϵ greedy mechanism, for various number of transmit antennas for relay node. Where, jake's model is used as fading channel, $V = 5km/h$ and γ_{s-r} =20dB.

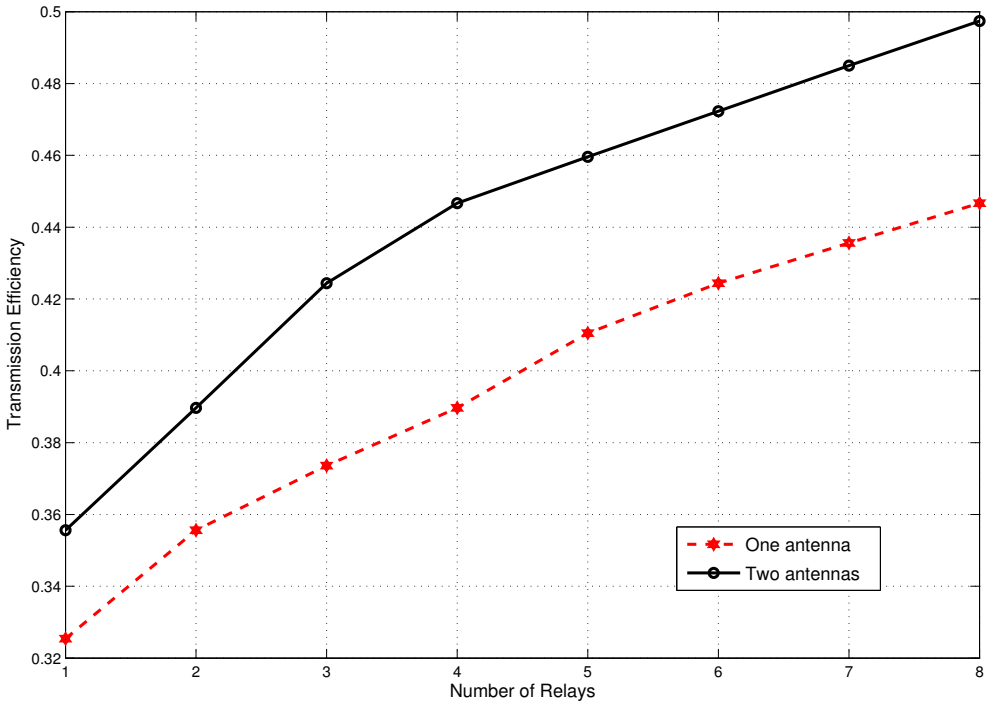


Figure 4.7: Transmission efficiency comparison of the system equipped with one and two antennas, where Q-learning using ϵ greedy mechanism and Jake's channel model is used where $V = 5km/h$.γ_{s-r} =20dB and γ_{r-d} =8dB

4.5.2 Effect of Exploration to Exploitation Ratio on Q-learning Antenna Selection

In this subsection, our algorithm operates in such a way that the destination chooses the exploitation mode more than the exploration mode, where the destination adopts the Q-learning algorithm for relay's transmit antenna combination selection. In this case, the destination operates in the exploration mode after certain fixed number of packets. Otherwise, the destination operates in the exploitation mode for relay's transmit antenna combination selection using the Q-learning table. In our simulation, we noted that the exploration mode helps the destination to make proper decision on future relay's transmit antenna selection. However, operating in the exploration mode is known to be expensive since in this case all reliable relay's transmit antenna participate in retransmission as our system is using TDMA communication for relay communications. Algorithm 4 summarizes

this source and relay's antenna combination selection protocol.

Algorithm 4 Effect of exploration to exploitation ratio on Q-learning based antenna selection algorithm

```
an integer = x_m
for (initial time to end time) do
    if counter == 0 or first packet then
        Choose source and relay's transmit antenna combination where all reliable relays are present
    else
        Choose source and relay's transmit antenna combination associated with the highest Q-value in the Q-table
        counter = counter + 1
    end if
    if counter ≥ x_m then
        counter = 0
    end if
    Update Q-table using (3.19)
end for
```

Tables 3.3–3.5 show the transmission efficiency for different exploration to exploitation ratio when $V = 5km/h$, $30km/h$ and $100km/h$. We set the SNR from source to relay link $\gamma_{s-r} = 20$dB and all other links are set at 8dB. From the results, we can see that for all three cases, the transmission efficiency changes with the change of exploration to exploitation ratio. It can be noted that, exploration to exploitation ratio 1/7200 and 1/7100 provide maximum transmission efficiency for cases, when $V = 5km/h$ and $30km/h$ respectively. Similarly, when $V = 100km/h$ exploration to exploitation ratio 1/3200 provides maximum transmission efficiency. It can also be noted that for $V = 100km/h$ exploration to the exploitation ratio increases since the channel changes very fast compared to the other two cases.

Fig. 4.8 shows the transmission efficiency comparison between the Q-learning using ϵ greedy mechanism and the effect of exploration and exploitation ratio on Q-learning when N_T=1 and N_T =2. From the results, we can see that both EER cases outperform the Q-learning using ϵ greedy mechanism. Results also show that, the relay equipped with more than one antenna offer better throughput performance compared to single antenna case

Table 4.2: Transmission efficiency for different exploration to exploitation ratio. $V = 5km/h$. $\gamma_{r-d} = 8$dB

Exploration to Exploitation ratio	Transmission Efficiency ($V = 5km/h$)
1/100	0.4410
1/1000	0.4479
1/2000	0.4511
1/3000	0.4774
1/4000	0.4843
1/5000	0.5177
1/6000	0.5249
1/7000	0.5552
1/7100	0.5707
1/7200	0.6013
1/7900	0.4977
1/8000	0.4407

Table 4.3: Transmission efficiency for different exploration to exploitation ratio. $V = 30km/h$. $\gamma_{r-d} = 8$dB

Exploration to Exploitation ratio	Transmission Efficiency ($V = 30km/h$)
1/100	0.4638
1/1000	0.4762
1/2000	0.4839
1/3000	0.4898
1/4000	0.4903
1/5000	0.5381
1/6000	0.5624
1/7000	0.5774
1/7100	0.5970
1/7200	0.5845
1/7900	0.4827
1/8000	0.4554

Table 4.4: Transmission efficiency for different exploration to exploitation ratio. $V = 100km/h$. $\gamma_{r-d} = 8$dB

Exploration to Exploitation ratio	Transmission Efficiency ($V = 100km/h$)
1/100	0.4453
1/1000	0.4654
1/2000	0.4839
1/3000	0.5533
1/3100	0.5734
1/3200	0.6076
1/4000	0.5381
1/5000	0.4524
1/6000	0.4674

as the multiple transmit antennas allow more combinations which help the destination to find the proper source and relay's transmit antenna combination from the Q-learning table.

Fig. 4.9 shows the effect of exploration-to-exploitation ratio on the Q-learning relay's transmit antenna selection algorithm when the channels are modeled using Jake's Rayleigh fading model with $V = 5km/h$, $30km/h$, $100km/h$ and the case of independent fading realizations. As the results show, our Q-learning algorithm utilizes the memory introduced in the time-varying channel to learn about the different channels, and uses this learning process to improve the relay's transmit antenna selection procedure as time elapses.

Fig. 4.10 shows the percentage usage of antenna combinations. As evident from these results, the number of relays transmitting antennas varies for our Q-learning based cross-layer approach as it maximizes the link-layer transmission efficiency. In other-wards, Fig.4.10 indicates the percentages of usage of relay's transmitting antennas that maximizes the transmission efficiency. From the results, one can see that at low SNRs, small number of relay's transmitting antennas are employed as the channels between relay's transmitting antennas to destination are poor. As the SNR increases, the channels become more reliable and more transmitting antennas are used in retransmission. Also one should note that as

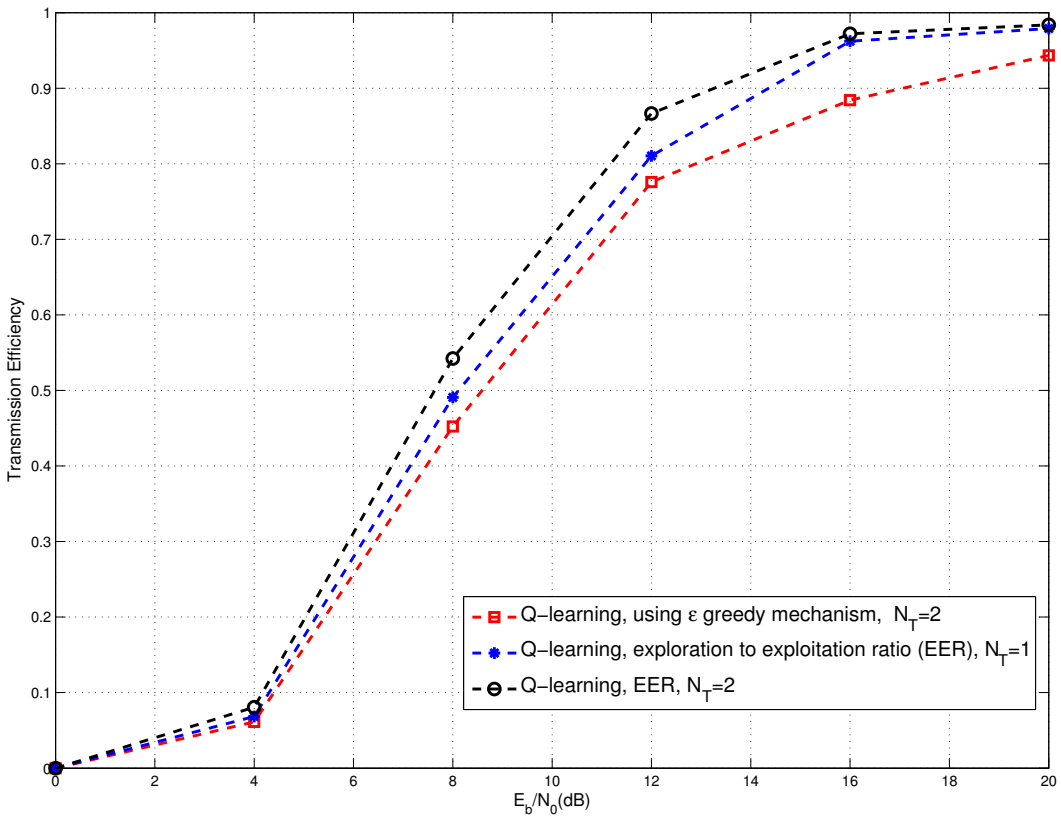


Figure 4.8: Transmission Efficiency Comparison of system using Q-learning based ϵ greedy mechanism and effect of exploration to exploitation ratio on Q-learning, when N_T=1 and N_T=2 under Jake's channel model where $V = 5km/h.\gamma_{s-r} = 20$dB.

the node speed goes high, the Q-learning acts on the limited memory of the channel and hence, more relay's transmitting antennas are employed relative to the case with lower node speeds.

From the bar graph we can see that, at SNR is 0dB the destination chooses single antenna combination most of the time when the node speeds are $V = 5km/h$ and $V = 30km/h$ as the total SNR is normalized to all links between relay's transmit antennas to the destination. As a result, all links between the relay's transmit antennas to the destination are poor. It can be also observed that, when SNRs are 4dB, 8dB, and 12dB there are few instances where two–six antenna combinations are used where the single antenna combination is more dominant.

Fig. 4.11 shows the transmission efficiency comparison for different SNR values

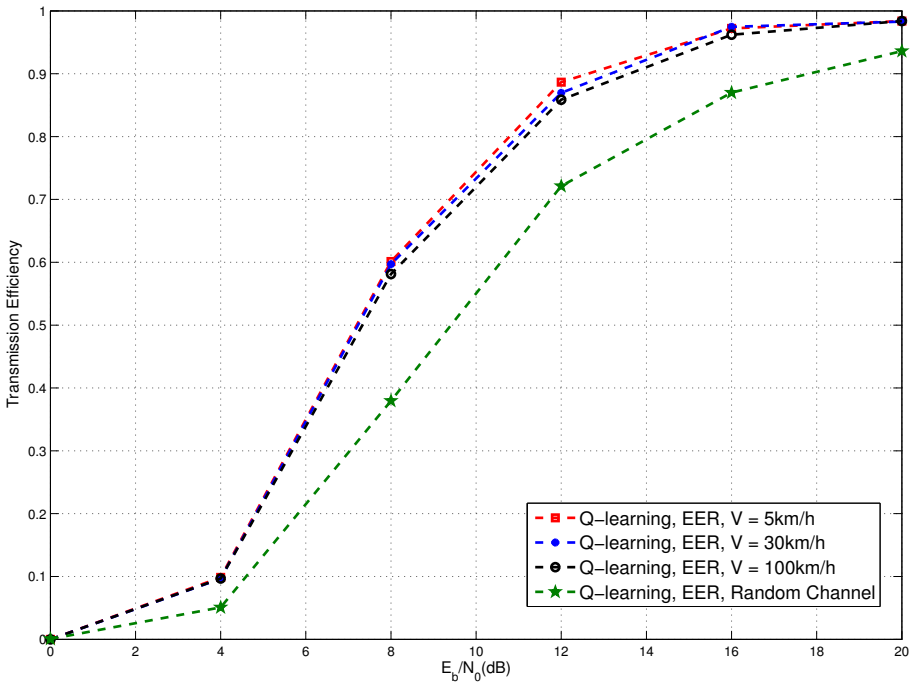


Figure 4.9: Effect of exploration-to-exploitation ratio with node speed $V = 5km/h$, $V = 30km/h$, $V = 100km/h$ and independent fading model with γ_{s-r} =20dB and N_T=2.

from the source to the relays. From the results, we can see that as we increase the SNR between the source to relay link, the transmission efficiency improves. This implies that, when the source to the relay links are poor a small number of relays correctly decode the source message. Hence small number of combination are available for the destination to maximize the transmission efficiency.

Fig. 4.12 shows the usage of antenna combination for different SNR values from the source to relay links. From the results, we can see that at γ_{s-r} = 5dB there is no instance where four relay combinations are used as γ_{s-r} = 5dB is too low to decode the source's message for all four relays. As noted before, in exploration mode, all reliable relay's transmit antennas are used to forward the source message to the destination and fill all entries in the Q-table. Therefore, when the S-R link is poor, single relay usage is always more than 90% as we use the selection combining technique and the proposed algorithm to update the Q-table. As mentioned before, only the best link is selected for the decoding in selection combining technique and according to the algorithm, if multi-antenna

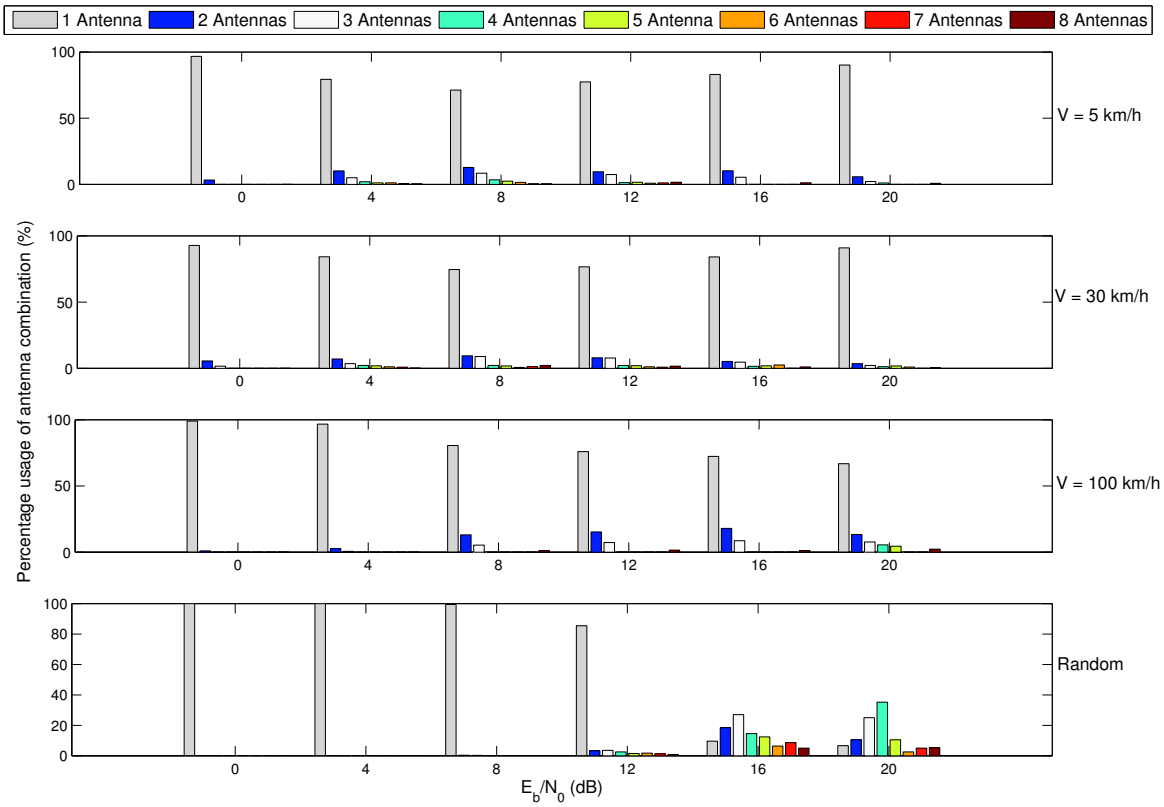


Figure 4.10: Usage of antenna combination for EER on Q-learning when channels are Jake's Rayleigh fading channel with node speed $V = 5km/h$, $V = 30km/h$, $V = 100km/h$ and EER on Q-learning when channels are random. γ_{s-r} =20dB and N_T=2.

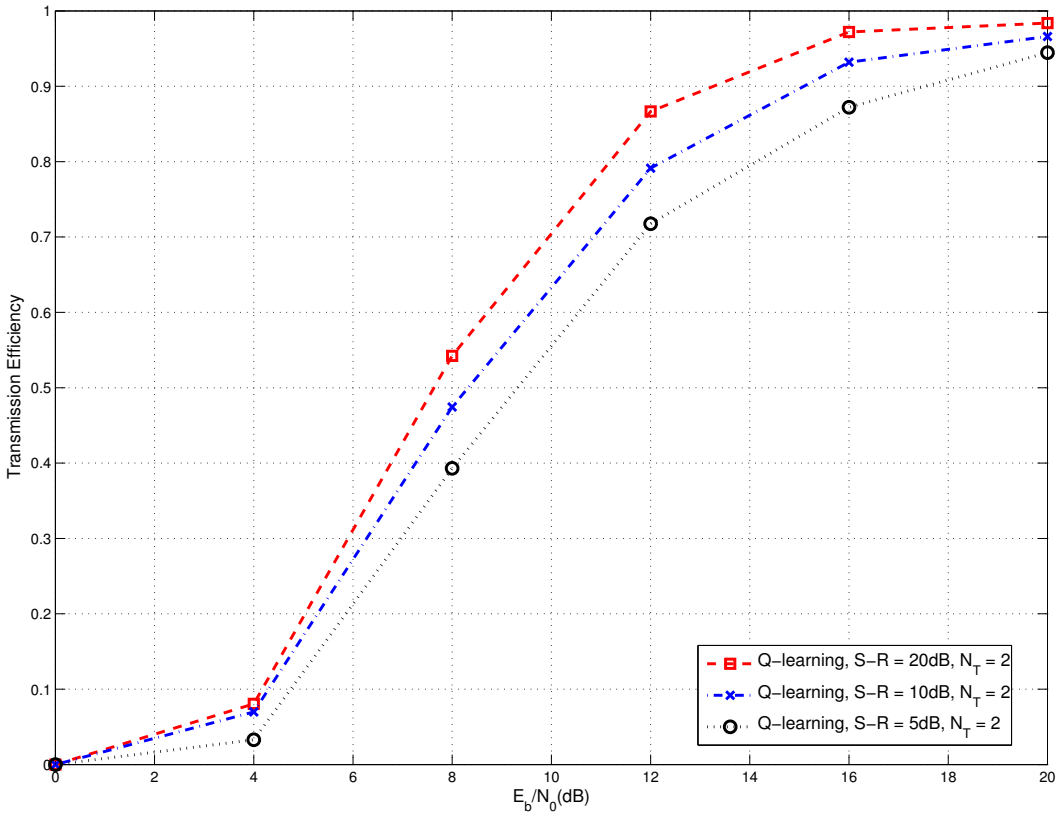


Figure 4.11: Transmission efficiency comparison for different SNR values of S-R link. Where, N_T=2, and Jake's model is used as fading channel, $V = 5km/h$.

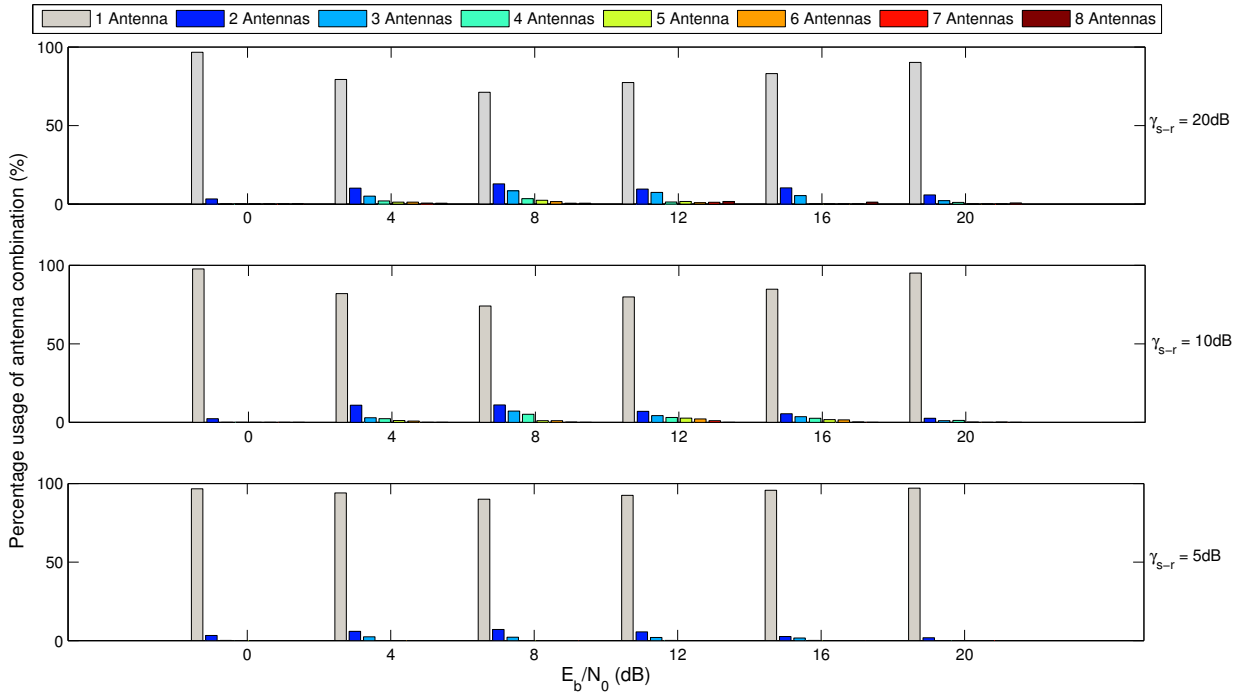


Figure 4.12: Usage of antenna combination for different SNR values of S-R link. Where, Jake's model is used as fading channel, $V = 5km/h$.

combination is selected by exploitation mode, then the destination not only updates it's specific combination but also updates all possible single antenna combinations by the estimate of Q-values. This helps the destination to choose the proper combination for the next packet transmission to maximize the link layer throughput by realizing the memory introduced by the fading channel model.

4.6 Conclusions

In this chapter, we have presented the Q-learning based cross-layer relay's transmit antenna selection scheme to maximize the link layer transmission efficiency. The proposed learning algorithm utilizes the memory introduced by the time-varying Rayleigh fading channel to learn and act on future relay selections and hence, improved throughput maximization relative to the conventional schemes with no learning involved. We have shown

that when relays are equipped with multiple transmit antennas the throughput performance outperforms the case with single transmit antenna. The performance of transmit antenna selection has been studied in this work. We have presented and compared the throughput performance with and without transmit antenna selection. The impact of the number of cooperating relays have been studied, where we have shown that as the number of cooperating relays increases, the throughput performance improves. Furthermore, the throughput performance for different source to relay link qualities has been studied. Results have shown that as the channel quality gets poorer, less reliable relays are available and the system throughput degrades. Our proposed system utilizes the channel resources more efficiently than the existing systems.

Chapter 5

Conclusions and Future Works

5.1 Conclusions

In this thesis we focused on studying the performance of cooperative relay networks. First we briefly reviewed cooperative diversity, different diversity combining techniques, Jake's Rayleigh fading model and an introduction on reinforcement learning. Throughout the thesis, we proved that using learning algorithms, reliable relay and reliable relay's antenna selection improve the performance of the cooperative network.

In chapter 3, the performance of Q-learning based cross-layer relay selection scheme was analyzed to maximize the link layer transmission efficiency. We studied the case for both time-varying Rayleigh fading channel modeled as Jake's model and also for independent fading model. We showed that, the proposed learning algorithm utilizes the memory introduced by the time-varying Rayleigh fading channel to learn and act on future relay selection to improve throughput performance relative to schemes where no learning is involved. We also have shown the effect of exploration-to-exploitation ratio, where the algorithm offers transmission efficiency gain over systems utilizing ϵ greedy mechanism. In addition to that, our proposed system uses the bandwidth efficiently as the algorithm chooses few number of reliable relays to maximize the throughput.

In chapter 4, multiple transmit antennas are considered for the relay nodes to analyze the Q-learning based cross-layer relay's transmit antennas selection scheme to maximize the link layer transmission efficiency. The performance of the network was studied for both the ϵ greedy mechanism and the optimized exploration-to-exploitation ratio using the Q-learning based relay's transmit antennas selection. We have shown that, the throughput performance of multiple transmit antennas employed in the relay node outperform the case when the relays are equipped with single transmit antenna. We also have presented and compared the throughput performance with and without transmit antenna selection. The impact of the number of cooperating relays has been examined, where we have shown that as the number of cooperating relays increases the throughput performance improves. Furthermore, the throughput performance for different source to relay link qualities has also studied. Results show that as the channel quality gets poorer the system employs less relays and hence system throughput degrades. We also found that, our proposed system utilizes the channel resources more efficiently and also provides improved transmission efficiency.

5.2 Future Works

In the sequel, here, we list some of the topics of interest.

1. In Chapter 3 and 4, we have considered cooperative networks operating in a particular frequency channel at a particular time instant. But, nodes can operate in multiple frequency channels simultaneously instead of adopting a single channel. Channel allocation problem for such system is an important research direction.

2. In our study we haven't used any channel coding techniques. Therefore, a study of the improvements when employing powerful channel codes such as turbo code is of

great interest.

3. The proposed cross-layer schemes are aimed at cognitive networks where learning techniques are a major part of such networks. However, our study was more general where it can be used for any cooperative system with some powerful nodes that can accommodate learning techniques. It is of interest to study the proposed cross-layer schemes in a cognitive network setting where both primary and cognitive (secondary) users exits.

4. Also, our proposed cross-layer schemes require additional computations and storage to perform Q-learning. A computational study would also be interesting to compare with conventional (i.e, no learning) techniques.

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