QUALITY OF SERVICE PROVISIONING IN BIOSENSOR NETWORKS

BY

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To my beloved parents, sisters and brothers..

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With the name of Allah, the most Beneficent, the most Merciful. Blessings and grace on Prophet Muhammad (SAW), Companions of Prophet and anyone who follows him.

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LIST OF ABBREVIATIONS

AP	Access Point
AWGN	Additive White Gaussian Noise
BASN	Body Area Sensor Networks
BER	Bit Error Rate
BS	Base Station
CSI	Channel State Information
DPLM	Dynamic Protocol for Lifetime Maximization
FDTD	Finite Difference Time-Domain
FSMC	Finite State Markov Chain
LP	Linear Programming
MDP	Markov Decision Processes
MQAM	M-ary Quadrature Amplitude Modulation
QoS	Quality of Service
RSSI	Received Signal Strength Indicator

RVI	Relative Value Iteration
SAR	Specific Absorption Rate
SNR	Signal to Noise Ratio
TIP	Temperature Increase Potential
WBAN	Wireless Body Area Networks
WSN	Wireless Sensor Networks

LIST OF SYMBOLS

γ	Discount factor
λ	Average arrivals at input of buffer
μ	State space of policies π
π	Policy
σ_t	Number of arrivals at input of buffer
θ_c	Channel gain in state c
A	State space of actions
B	State space of buffer occupancy
B_{size}	Buffer size
c	Channel state index
D_O	Average delay constraint for thermal increment model
D_t	Instantaneous buffer delay at time slot t
d_t	Average buffer delay at time slot t
E_b	BER constraint

F	Number of channel uses per time slot
G	Size of incoming samples in terms of bits
J_p	Objective function
K	Number of channel states
L	Average loss rate
L_O	Average loss rate constraint for thermal increment model
L_t	Loss rate at time slot t
N_O	Channel noise (AWGN)
P	Transmission power
P_O	Average transmission power constraint for thermal increment model
R	Reward for average transmission rate maximization
T_t	Thermal increment at time slot t
W	Bandwidth
x	Decision variable
Z	Maximum incoming samples
${D_O}^v$	Average delay constraint for strict temperature model
${L_O}^v$	Average loss rate constraint for strict temperature model
${P_O}^v$	Average transmission power constraint for strict temperature model

THESIS ABSTRACT

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TITLE OF STUDY: Quality of Service Provisioning in Biosensor Networks

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Biosensor networks is an emerging field of Wireless Sensor Networks (WSN) that consists of small biological sensors that are implanted inside the body of the subject. These biosensor nodes can take measurements of various biological processes occurring inside the subject and report back to the Base Station (BS). The BS is responsible for taking necessary actions based on the received data. Biosensor networks find there use in different medical processes like automated drug delivery, heart beat rate monitoring, and temperature sensing etc.

Wireless transmissions in biosensor networks produce heat in the surrounding tissues of the subject in which they are implanted. The heating effect is cancelled by the thermoregulatory system of the subject. However, excessive transmissions can cause the tissue damage due to reduced blood flow. Hence, there is a need to control these wireless transmissions to prevent damage to the tissues of the subject.

Another important parameter for biosensor networks that has not been discussed before is the Quality of Service(QoS). Different medical operations require different QoS requirements which the biosensor networks need to provide.

In this work, we propose a new model for biosensor networks that takes into consideration the buffer occupancy of a biosensor node alongside changing wireless channel statistics. Based on this model, we develop optimal transmission policies that maximize the average transmission rate and minimize the average transmission power under different QoS constraints like average delay and average loss rate etc.

Temperature increase caused by excessive transmissions is controlled using two different models, the average thermal increment model and the strict temperature model. The system is analysed using Markov Decision Processes (MDP) and solved using Linear Programming (LP) approach. The optimal policies calculated are then compared with a greedy policy for performance analysis. The optimal policies outperform the greedy policy in both the network lifetime and transmission rate objectives. The thermal behaviour of the optimal policies for the two models is also discussed at the end. This work provides a new approach for QoS provisioning in biosensor networks while ensuring the tissues of the subject remain in the safe operating region.

خلاصة أطروحة

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عنوان الدراسة: جودة توفير الخدمة في شبكات الاستشعار البيولوجي

الميدانية الرئيسية: قسم هندسة الكمبيوتر

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تعتبر شبكات الاستشعار البيولوجي نوع ناشئ من شبكات الاستشعار اللاسلكية والتي تتكون من أجهزة استشعار بيولوجية صغيرة يتم زرعها داخل جسم الإنسان أو الحيوان. يمكن لهذه الشبكات أخذ قياسات من العمليات البيولوجية المختلفة التي تحدث داخل جسم الإنسان وإرسالها إلى قاعدة مركزية من أجل التحليل وأخذ القرارات. يمكن استخدام هذا النوع من الشبكات في تطبيقات طبية مثل الحقن الآلي للأدوية ورصد معدل ضربات القلب و درجة الحرارة.

تقوم شبكات الاستشعار البيولوجي برفع درجة حرارة الجسم الداخلية بسبب نقلها للبيانات بطريقة لاسلكية. وكما هو معلوم فقد يؤدي ارتفاع درجة الحرارة المفرط لتلف الأنسجة الداخلية في الجسم. ويعتبر هذا السبب عائق رئيسي أمام التطبيقات الطبية الحديثة. فمثلاً قد تؤدي فترات التبريد الطويلة بسبب ارتفاع درجة الحرارة لخلل في جودة الخدمة وبالتالي لفشل التطبيق الطبي بالكامل.

نقوم في هذا العمل بإقترح نموذج جديد لشبكات الاستشعار البيولوجي والذي يأخذ بعين الاعتبار السلوك العشوائي لوصول البيانات والقناة اللاسلكية بين الشبكة والقاعدة المركزية. يمثل حل النموذج الرياضي المقترح الطريقة المثلى التي يجب اتباعها عند تشغيل هذا النوع من الشبكات داخل جسم الإنسان. وتتغلب طرق التشغيل المثلى على الطرق التي تعتمد على الإرسال الدائم للبيانات أو تلك التي لاتأخذ بعين الإعتبار عشوائية وصول البيانات داخل الشبكة. وتحافظ ايضا على مستوى معقول من جودة الخدمة.

CHAPTER 1

INTRODUCTION

1.1 Sensor Networks

In the past decade, technological growth in software and hardware devices have led to the development of tiny sensor devices that are economical and utilize low energy. A large collection of wireless sensor nodes, when spread across a geographic location, form a Wireless Sensor Network which can be used for various applications like process monitoring, surveillance activities, seismic monitoring and industrial automation etc [1]. Wireless Sensor Networks (WSN) are responsible for data collection, its processing and propagation. Excessive amount of research has already been done in the field of WSN to tackle different challenges faced by these networks like energy efficient operation, responsiveness,robustness and self-configurability etc.

1.2 Biosensor Networks

Biosensor Networks is a branch of WSN that utilizes small biosensors for wireless communication. Biosensors are small communication devices which employ biological materials such as enzymes and antibodies as sensing elements. A collection of biosensors are implanted inside the body of the subject to form a biosensor network that can be used to monitor and observe various biological processes and detect anomalies inside the subject. This information is relayed back to a BS to provide necessary treatment. Biosensor networks find there use in various daily medical tasks like sensing body temperature, calculating heart beat rate and automated drug delivery etc. Biosensor networks are powered by either rechargeable batteries or through electromagnetic waves. Body Area Sensor Networks (BASN) also known as Wireless Body Area Networks (WBAN) is also a relevant field in health monitoring using wireless technologies. Small and lightweight sensors are attached to the outer surface of the subject [2]. Biosensor networks differ from WBAN since the sensors are implanted inside the body instead of outer surface. Various new challenges are introduced by these special WSN which are discussed next.

1.3 Design Challenges for Biosensor Networks

Biosensor Networks contain all the technical challenges introduced by normal WSN. In addition, they propose new ones that are unique to them. A major challenge to realizing the full potential of biosensor networks is the heat they generate as a result of power dissipation and wireless radiation. Unlike common wireless sensor networks (WSN), biosensors have limited energy and they operate inside the body of the subject. Each biosensor transmission generates heat. This heat increases the temperature of the surrounding tissues of the subject. The effect of the generated heat is balanced by the thermoregulatory system. However, excessive transmissions may result in generated heat being greater than what can be drained by the thermoregulatory system. The temperature increase if exceeds a certain threshold can cause adverse effects on the tissues and may damage them because of reduced blood flow. In such case, the biosensor node is shut down in order for the tissues to cool down and attain normal body temperature.

As a consequence, the maximum safe temperature level which the tissues can withstand becomes an important factor while operating biosensor networks. Therefore, there is a need for intelligent thermal management techniques which can mitigate the thermal effect on the tissues. Such techniques would, for example, enable long-term measurements to be performed and thus help in avoiding the prohibitive cost of continual hospital visits.

Biosensor networks like WSN are required to be energy efficient as well. Making the system energy efficient has the added advantage of lesser wireless transmissions which result in better thermal management of the system as well. So, minimizing the overall energy utilization by the system causes the system to operate in safe temperature zone.

On the other hand, increased transmissions provide better accuracy in the real time system being implemented by the biosensor network and increase its robustness. So there is a need to optimize the transmission schedule of biosensors to prevent damage to the subject's skin tissues and at the same time make the system as robust as possible. All these contradicting challenges need to be addressed. An optimal operating policy for biosensor network based on these conflicting objectives needs to be formulated which maximize the system performance and provide better QoS.

1.4 Quality of Service Provisioning in Biosensor Networks

Future medical healthcare will require numerous services with different Quality of Service (QoS) requirements. The changing behaviour of the wireless channel and random arrivals to biosensor node pose a significant challenge in achieving this goal [3]. In biosensor networks minimizing the power consumption is an important objective for battery operated devices. It has an added advantage of reducing the operating temperature of the biosensor node. Similarly increasing the sample transmissions can increase the robustness of the system. In order to provide these varying services, different QoS parameters are considered which can affect performance of the system. Very little work has been done in providing QoS provisioning in biosensor networks. In the recent past, the main focus has been on minimizing the average temperature increase of the system [4] [5] [6] without considering other QoS parameters that may affect system performance.

An important QoS parameter that can affect the system performance is the delay experienced by the incoming samples at the input of the buffer. Different users will experience varying QoS depending on the delay experienced by each of them. So, delay at the input of buffer is an important parameter that needs to be included in the system design.

Similarly, the number of samples lost at the input of buffer is also an important QoS factor to the users requiring robustness and quick system response. Reducing the sample transmissions to save energy can cause number of samples in buffer to increase which consequently causes the loss of samples. Hence,when minimizing the overall power consumption, QoS provisioning requires that the loss rate shouldn't exceed certain limit.

Besides these above mentioned QoS parameters, an additional QoS constraint required when maximizing the sample transmissions is the thermal increase QoS constraint. Each transmission causes the temperature of the surrounding tissues to increase. Restricting the increase in temperature of surrounding tissues causes the system to operate in safe zone. An accurate description of thermal increase constraint is described in later chapters.

Unfortunately, all the current system models used to represent a biosensor network does not take into account the state of buffer as a system parameter. As a result, important QoS parameters like delay and loss rate are not taken into account. The inclusion of buffer state as a system parameter can provide an accurate picture of the biosensor node and also help in providing better QoS provisioning for different applications in biosensor networks which can help in targeting specific class of diseases based on their QoS requirement.

1.5 Thesis Outline

This thesis presents a new system model for biosensor nodes that introduces buffer state as part of the system model for biosensor networks. The system is formulated as a cross layer optimization problem having fixed transmission buffer over a slowly varying Rayleigh channel. The system can be accurately represented by an MDP. Two different MDP models are proposed that vary based on the way they handle the temperature variations in the system. In first model, the system state consists of channel and buffer state. Temperature variations are introduced as a thermal increment constraint. In the second model, a strict temperature constraint is proposed by including temperature as part of the system model. The system state in this case consists of channel, buffer and temperature state. This provides an upper bound on the operating temperature and makes sure the biosensor never exceeds limits. Various QoS parameters like average buffer delay, average loss rate and average thermal increment are used to achieve different objectives like minimizing average power consumption and maximizing average number of sample transmissions. In order to obtain optimal operating policies using these objectives and constraints, LP toolbox is used to model the MDP [7] in MATLAB [8]. Once the optimal policies are obtained, the system is simulated and performance is compared with greedy policy. The safe operation of biosensor node is also observed during analysis. Our contribution can be summarized as follows:

1. Proposing a new model for biosensor networks that incorporates the effect of traffic on system performance,
2. Study the effect of different QoS constraints like loss rate and buffer delay, and
3. Capturing the thermal effect by proposing an average thermal increment model and a strict temperature model

1.6 Summary

This thesis presents a new system model for biosensor networks that takes into consideration the buffer state as part of the system model. Different optimal policies are calculated for achieving certain objectives under various QoS constraints. The organization of the work is as follows, a detailed literature review in this area is provided in Chapter 2. Chapter 3 provides a background information to the tools used for evaluating the optimal policies. The proposed model that incorporates traffic into the system along with different QoS parameters is discussed in Chapter 4. Chapter 5 describes the results obtained by solving the system for optimal policies and simulating the results. Conclusions and future work are discussed in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

There is a growing body of work done in the field of wireless network technologies to provide cost effective solutions for health care industry. Long-term health care monitoring is a daunting task and this requires huge amount of cost and labor work [9]. The evolution in wireless technologies have led to a cost effective realization in solving such problems. WSN consists of small, energy constrained sensors which are used to monitor various phenomenon's and report back to Base Station (BS). A lot of work has been done to improve the performance of wireless sensor and cellular networks [10], [11], [12], [13]. Bio-sensor network is field of WSN which deals with observing biological processes within the subjects in which they are placed. The similar field to biosensor networks;i.e., WBAN has also seen recent development in energy control methodologies. This chapter provides a review on the various QoS improvement techniques relative to our study that have been deployed in the fields of wireless cellular networks, WSN, WBAN and biosensor networks.

2.1 QoS Provisioning in Wireless Networks

Support for various QoS requirements like average packet loss, average delay, Bit Error Rate etc. are essential in development of future wireless networks. However, there are varying challenges faced in doing so e.g. limited battery energy and time varying nature of wireless channel etc. Cross layer optimization techniques have been proposed in literature to tackle these issues. Authors in [14] handle the issue of time varying nature of wireless channel by putting constraints on different system parameters like data rate, modulation schemes and transmission power.

The QoS trade-off's between average transmission power, average packet dropping probability and average buffer delay for optimal transmission scheduling is studied in [3]. The authors consider a cross-layer optimization problem for wireless communication networks having a finite size transmission buffer over a time varying correlated fading channel. A decentralized time-slotted single user system is presented. The channel is assumed to be slowly varying having Rayleigh distribution which can be modeled as Finite State Markov Chain (FSMC) [39]. The system is formulated as both constrained and unconstrained MDP with average cost criteria. Unconstrained MDP formulation is solved using Relative Value Iteration (RVI) algorithm while LP approach is used to find optimal scheduling policies for constrained MDP. In unconstrained MDP optimization, weighted sum of three QoS parameters average power, average delay and average packet dropping probability are minimized. However, in constrained MDP formulation each of the objective is minimized one by one while enforcing constraints on the remaining parameters. Although unconstrained MDP produce superior deterministic policies as compared to constrained MDP which produce randomized policies, solution of constrained MDP using LP is computationally fast as compared to RVI algorithm and also able to handle large number of constraints. For cases involving limited resources where its not possible to use optimal policies, the authors propose an sub optimal log scheduling policy that is independent of the wireless channel statistics. The performance of sub optimal scheduler is shown to be close to optimal scheduler over different fading rates, number of action sets and type of arrivals at input of buffer. The work provides great insights into modeling of slowly faded Rayleigh distributed channel and buffer occupancy as a MDP and optimization of various QoS parameters are also represented in detail which provides significant help in developing a new system model for biosensor networks.

A large amount of work in optimizing the transmit power control for wireless ad-hoc networks is already done in [15] [16] [17]. They propose various optimal transmission policies under various constraints. Authors in [12] deal with the optimization of cellular networks by considering an uplink power control problem. QoS of the cellular networks is improved by maximizing network lifetime and throughput with the help of controlling a discrete set of power levels for transmissions based on available channel state information. Two cases for acquiring channel state information are considered, centralized and decentralized. In decentralized case, a single mobile unit chooses its power level based on the information from its channel to base station information. However, in centralized case, all the channel information of mobile units in the system is captured by the base station and based on that, an optimum power level is chosen for each of the mobile units. In both the cases, two type of optimizations are proposed;i.e., Cooperative and non cooperative optimizations. In cooperative optimization a common objective is chosen to optimize whereas in non cooperative optimization each mobile unit optimizes its own objective independent of the status of other mobile units. The system is formulated as a linear programming problem and is solved to obtain optimal policies that maximize the objective. The authors also provide a numerical example for communication between two mobile units with the base station. Power control is one of the objectives that are considered in this thesis during the development of optimal policies for bio-sensor network and non cooperative optimization provide ample benefits in developing the MDP models biosensor network that we present.

2.2 Optimization in Wireless Sensor Networks

Various design metrics have been used in optimization of WSN e.g. mean square error [18], [19], throughput [11], and network lifetime [20], [21], [22], [23]. Wireless sensor network are operated on battery's and need to operate for long period of times since most of the applications requires remote deployment. So saving the power consumption and maximizing network lifetime is of prime importance.

Maximizing network life time of a wireless sensor network is dealt in [13] by presenting optimal transmission scheduling policies for sensor nodes. The problem is formulated as a shortest path MDP. The paper introduce three different channel information structures: global Channel State Information (CSI), channel statistics, and local CSI. The system is assumed to be time-slotted. The Access Point (AP) initiates the data collection process in each time slot by selecting a subset of sensors for transmission according to an optimum policy. In global CSI structure, the scheduler has channel realization information of all nodes in the network which causes increased implementation overhead. Whereas, in channel statistics structure, channel distribution of various nodes in the network is realized by the scheduler in finding the optimal policies. Local CSI provides the advantages of using CSI without the implementation overhead. Each node, based on its own channel state information and residual energy, determines and efficiency index. The nodes with high efficiency index are scheduled for transmission in the next time slot using distributed opportunistic carrier sensing scheme [24]. The efficiency index is calculated according to a scheduling algorithm developed in [25] called Dynamic Protocol for Lifetime Maximization (DPLM). Various trade-off's between the channel information structures are discussed to maximize network lifetime. In our work, the biosensor nodes use local CSI in order to develop an optimal scheduling policy under various conflicting constraints.

2.3 Optimal Power Control in Wireless Body Area Networks

Body Area Sensor Networks (BASN) also known as Wireless Body Area Networks (WBAN) is also a relevant field in health monitoring using wireless technologies. Small and lightweight sensors are attached to the outer surface of the subject [26]. These networks have less effect on tissues as compared to biosensor networks therefore not much research has been done in temperature control for such networks. Various prototype devices have been developed for WBAN, such as MicaZ motes [27] which are part of Harvards CodeBlue project [28] and Toumaz Sensium Digital Plaster chips which are operated by small printed batteries [29]. These sensor devices have very limited energy resources and since communication is the most energy consuming operation which they perform [30], careful transmission power control is required to operate the devices.

As far as WBAN are concerned, Authors of [9] optimize the network life time of WBAN by the use of dynamic radio transmit power control. Potential gains of using dynamic radio transmission to achieve better network lifetime are quantified by comparing them against offline energy saving policies under a given reliability. The authors provide offline transmission policy by providing a comprehensive research regarding rapid change in wireless channel quality. The Received Signal Strength Indicator (RSSI) is used to explain the states of wireless channel when subject is observing three scenarios;i.e., normal walk, slow walk and resting. The optimal transmission power is defined as the lowest transmit power required to achieve a minimum required RSSI. In off-line optimal transmission scheduling the choice of optimal power is done off-line by observing the RSSI of different scenarios. Through empirical evidence, it is reported that the ideal environment for reducing the energy consumption is when the patients are at rest. In developing online power control policies, the channel state information is provided by the base station through a feedback channel which is assumed to be perfect. The base station measures the RSSI for each packet and transmits the information back to the sensor mote in acknowledgement packet. The online policy is built by maintaining a running average of RSSI and comparing it against certain threshold parameters to increase or decrease the transmit power. The parameters are adjusted to obtain trade-offs between energy savings and reliability of the system which make them suitable for different applications depending on operating conditions. The proposed scheme is practically tested on real WBAN motes at the end. The paper provides a detailed information regarding the changing statistics of the wireless channel and shows that power control is an important parameter in maximizing system performance in WBAN.

2.4 Linear Programming Solvers for MDP's

Most of the systems proposed in previous work use MDP to for obtaining optimal policies. Normal approaches to solution of MDP use policy iteration and value iteration methods. But these methods suffer when the system state space increase or the number of constraints are increased. LP approaches have been used in the past to solve system with large constraints and state space. So, we will use LP approaches on the MDP formulated system model. The authors of [7] propose linear programming (LP) solvers for MDPs. The solvers are developed in Java and work for the discounted cost as well as average cost criteria in MDPs. The results obtained are compared with value and policy iteration algorithms for the solution of MDPs and indicate a significant performance boost when using LP solvers. The papers describes in detail how to formulate constrained MDP with average cost criterion as a LP model and setup its parameters.

2.5 Performance Optimization in Biosensor Networks

In bio-sensor networks, additional constraints are introduced which increase the complexity in developing optimal policies for providing QoS [31] [32]. Most important of these is the temperature constraint. Radio transmissions in biosensor networks cause increase in temperature of the tissues surrounding the subject. Ensuring the system operates in safe operating zone is of prime importance in biosensor networks.

Cluster based approaches to handle the temperature increase in biosensor networks have also been proposed in literature. Specific Absorption Rate (SAR) is parameter used in literature to represent the rate at which radiation energy is absorbed by human tissues. It is shown in literature that exposure to to SAR of $8W/Kg$ in single gram of tissue for 15 minutes may result in tissue damage in the head or torso of subject [33]. Similarly sensitive organs having biosensor nodes implanted inside them are even more sensitive to temperature increase and might be damaged with lesser increase in SAR [34]. Temperature Increase Potential (TIP) is parameter introduced in [35] to reflect an estimated increase in temperature of biosensor nodes in the network. TIP based on Pennes bioheat equation [36] and the Finite Difference Time-Domain (FDTD) method [37]. The authors use SAR to model the exact temperature increase in biosensor networks by taking into consideration the heating effects caused by the power dissipation due to recharging of biosensor nodes, sample transmissions and losses in sensor circuitry. TIP is used to estimate the temperature increase value of each sensor node by taking into account the rotation sequence, sensor location and effect of other nodes in the network. P_{ij} is defined as TIP at node j due to node i. By taking the effect of all other biosensor nodes in the network, TIP for node j can be calculated. A rotating cluster policy for optimization of thermal management of the biosensor network is proposed . Since the cluster selection process requires significant resources, a genetic algorithm is proposed at the end which provides a near optimal rotation sequences that minimizes temperature increase. This paper provides an detailed model for predicting the temperature increase in biosensor nodes but doesn't take into account the changing statistics of the wireless channel and the limited buffer space. In our work we present an abstract value of temperature increase instead of getting the exact value to simulate the behaviour of optimal policy.

The heating issue of biosensor nodes is addressed in [5] [4]. The authors optimize the network lifetime under strict temperature constraints by considering different amounts of initial energy. The system consists of sensor nodes whose transmissions affect the temperature level of surrounding sensors as well. The system is modeled as a discrete time MDP that grows in discrete time steps over time. During each time slot, the scheduled sensor undergoes a change in its energy and temperature according to its action. The unaffected biosensors temperature is assumed to decrease constantly whereas temperature increase for those that are affected is considered to be directly related with the scheduled sensor for transmission. The system is solved to obtain an optimal operating policy that maximizes the network lifetime while keeping the system in safe temperature zone to avoid tissue damages.The optimal policy obtained by solving the MDP is compared with the TIP and residual energy based transmission scheduling policies. The results obtained indicate that the optimal policy performs better as compared to other two policies. Fig. 2 shows the system observed in maximization of network life time.

Optimization of biosensor networks by increasing the number of transmitted samples is addressed in [6]. Since biosensor networks operate in a real time environment, increasing the robustness of the system by providing timely and accurate readings certainly improves the performance of the system. The model of the biosensor network proposed is shown in Fig. 3. Biosensor is implanted inside the

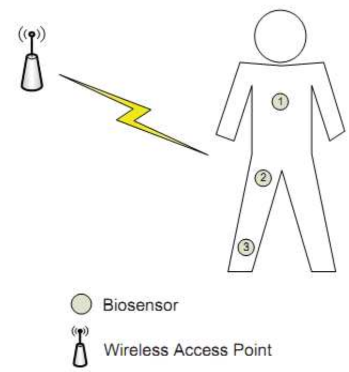

Figure 2.1: Network Lifetime Optimization in Biosensor Networks

body of the subject. The control signals are initiated by the base station which also controls the power source. This system is modeled as a discrete time MDP having current energy and transmission power as system states. Temperature is also introduced as a strict constraint and is part of states set. The actions are controlled by the base station and consists of transmit sample, sleep and recharge biosensor node. The authors evaluate an optimal policy by solving the system using value iteration algorithm with average reward criteria that maximizes the samples transmitted by a biosensor network against greedy and heuristic policies. The heuristic policy presents two control parameters that allow dynamic selection of actions. The results achieved through heuristic policies are very close to the optimal one and can be used where evaluation of optimal policy is not feasible. The model, however, does not take into account the changing state of wireless channel and the varying amount of traffic input to the biosensor nodes.

The papers discussed in [5], [4] and [6] provide an accurate model for biosensor networks by considering both power and energy constraints. The models, however, does not consider the effect of changing wireless channel as well as the traffic input

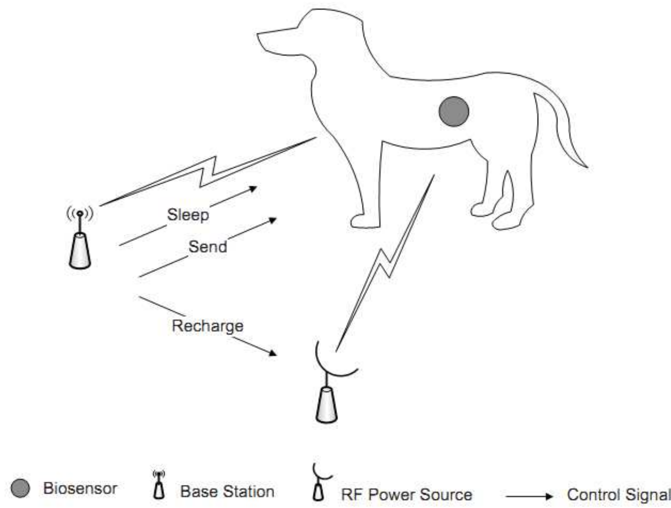

Figure 2.2: Maximizing Sample Transmissions in Biosensor Networks

at the biosensor network. In this thesis work, we propose a new model for biosensor networks that incorporates traffic and changing wireless channel statistics into the system. New constraints are introduced by the addition of traffic, which are then solved to obtain optimal operating policies. The optimal policies are simulated and results are compared with a greedy policy to investigate the effect on QoS. The thermal effect of obtained policies and how it can limit the performance is also discussed at the end.

2.6 Summary

In this chapter, research and previous work related to QoS provisioning in biosensor networks are presented. In literature, there isn't much work done in providing better QoS for biosensor networks. However, work done in the field of other wireless network provide ample base to propose a new model for biosensor networks that is able to provide varying QoS requirements. Thus contribution of this thesis work adds a new dimension in biosensor networks that is able to handle various issues related to packet loss and changing wireless channel statistics.

CHAPTER 3

BACKGROUND

This chapter presents the background information about the tools used to study the new system model proposed for the biosensor networks. We shall use the framework of MDP to study interaction between the different components in the system. In order to solve the MDP representation of the system we use LP approach in MATLAB[8]. Some background information on both these topics is discussed in this chapter.

3.1 Markov Decision Processes

MDP have been used widely in solving variety of problems related to data communication, computer networks and robotics. MDP are used in modeling of time varying dynamic systems. A necessary property that any markov process or a chain satisfies is that the effects of an action taken in a state depend only on that state and not on the prior history of the system. This property is called markov property. In short, the markov property means the memory-less property of a

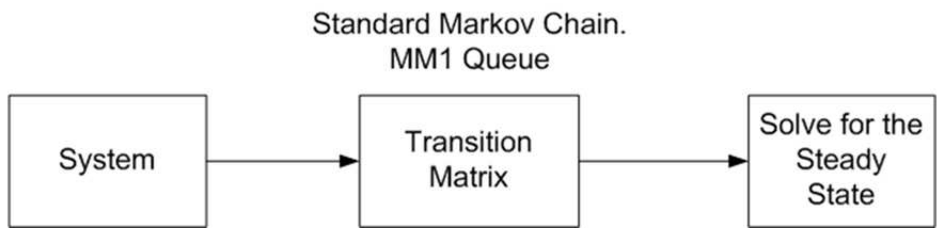

Figure 3.1: Solving Discrete Markov Chains

stochastic process. In a simple discrete markov chain, given the current state of the system, a one-state transition matrix gives the probabilities for what the state will be next time. Given this transition matrix, one can describe the behavior of the system by finding the steady state probabilities. Many queuing systems can be modeled using markov chains. This process is shown in Fig. 3.1.

Now in order to design the operation of a discrete time Markov chain so as to optimize its performance, rather than passively accepting the design of the Markov chain and the corresponding fixed transition matrix, we get proactive. For each possible state of the Markov chain, we make decision about which one of several alternative actions should be taken in that state. The action that is chosen affects the transition probabilities of the system as well as the immediate costs (or rewards) and subsequent costs from operating the system. We want to choose the optimal set of actions for all the states of the system when considering both the immediate and subsequent costs. The decision process for doing this is referred to as a Markov Decision Process (MDP). So to summarize, we can say that a Markov Decision Process (MDP) model contains:

1. A set of possible system states S,

2. A set of possible actions A,

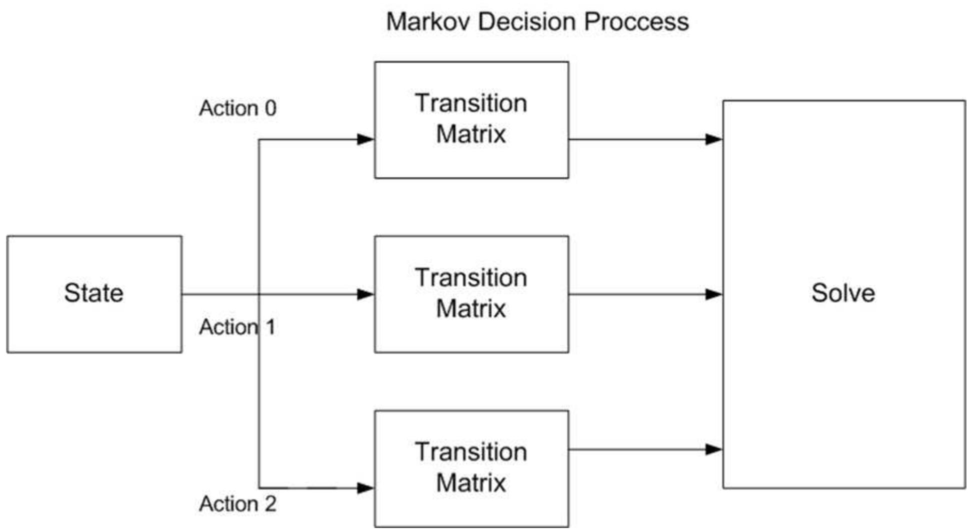

Figure 3.2: General Description of Markov Decision Process

3. A real-valued reward or cost function for all the possible state-action pairs and

4. A system state transition probability matrix for all the system states.

Fig. 3.2 gives a general description of various components of a MDP model.

Solving the MDP model ends up with a rule that provides information regarding which action to choose in each state of the system. So given an MDP our objective is to determine an optimal policy according to some cost criterion that will maximize our reward. Once the optimal policy is determined, it will decide which action to perform in each state of the system such that it maximizes our reward criteria. The optimal policy will help to build an optimal transition probability matrix that can optimally describe the behaviour of the system and improve its performance. Fig. 3.3 shows this optimal policy behaviour and how it builds optimal transition probability matrix.

In terms of System state probabilities, the optimal transition probability ma-

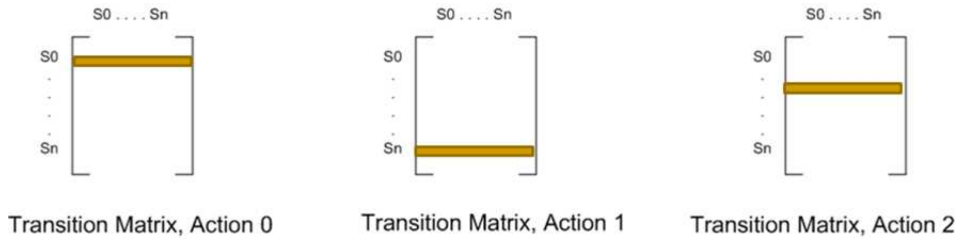

Figure 3.3: Optimal Transition Probability Matrix

trix is formed by picking for each system state the optimal row from all the transition probability matrices formed for all actions.

Objective functions map the infinite sequence of rewards to real valued numbers e.g. total reward, average reward and discounted reward can be considered as objective functions to obtain the policy. In this thesis work we consider the average reward criterion to solve the MDPs. In order to solve the system for optimization, it is required to solve the Bellman's equation . The standard form of this equation is represented as

$$V_n(s) = \underset{a \in A}{\max / \min} \left[R(s,a) + \gamma \sum_{s' \in S} P(s'|s,a) \times V_{n-1} \right] \tag{3.1}$$

where γ is the discount factor and for average reward criteria it's value is one. $R(s,a)$ represent the reward for performing action a in state s, $P(s'|s,a)$ represents the transition probability of choosing action a in state s of the system and moving to a new state s'. n represents the iteration index during optimization process.

There are various methods of deriving an optimal policy for an MDP like exhaustive enumeration, linear programming, value iteration and policy iteration. In policy iteration we start with an arbitrary policy π_0 and carry out multiple iterations. In each iteration we calculate the reward of following the current policy and compare it with the current reward of the system. If the action suggested improves the reward, we update the policy and start next iteration. The process stops when there is no improvement in policy possible.

In iterative approaches to solve the MDP models, one needs to incorporate all the constraints in the system into the cost function as a weighted form. This can be difficult if the number of constraint is large. For such type of problems LP approaches are able to better handle the large number of system states and constraints. In this thesis work we use LP approach for solving MDPs to efficiently control the constraints in the system.

3.2 Linear Programming

LP is a technique for determining optimal solutions to mathematical problems which can be expressed as linear equations. A linear program consists of a set of variables, a linear objective function which indicates the effect of each variable on the required outcome, and a set of linear constraints which limit maximum or minimum values the variables can take. Finding the optimal solution of the problem involves determining the values of these variables that optimize the objective function and keeps all the constraints within bounds. The most important part of LP is formulating a real world problem into a linear program. Formulation is the process of translating a real-world problem into a linear program. Once the problem is accurately formulated according to LP requirements, the process of obtaining the solution can be done simply through a computer program. There are many LP tool boxes available in various programming languages like C++, JAVA, MATLAB etc. This helps the researchers to focus on accurate modeling of the system, the rest is handled by the tool box. The essential parts of a linear program are explained below.

3.2.1 Decision Variables

The variables in a linear program are the set whose values need to be determined in order to find the optimal solution. These variables are also called decision variables because the optimal solution is determined based on there values. Decision variables represent the utilization of resources. For example, in biosensor networks a decision variable might indicate the average cost of transmitting certain number of samples in a particular system state. Defining decision variables is of prime importance in accurate modeling of real world problems as a linear program.

3.2.2 Objective Function

The objective function in a LP model is the parameter that we want to optimize. The optimization can be maximization or minimization of the objective function. The values of decision variables are determined so as the objective is achieved.LP modelling is a extremely general technique, and its applications are limited mainly by our imaginations. In our work the objective functions are the average transmission power and average sample transmissions which will be discussed later. In short the objective function indicates how each variable contributes to the value to be optimized in solving the problem. The general form for optimization of objective function in a linear program is shown in.

$$\max / \min \sum_{i \in N} x_i \times R_i \tag{3.2}$$

Where x_i represent the i^{th} decision variable and R_i represent the objective function coefficient matrix corresponding to i^{th} variable. The coefficients of the objective function indicate there contribution to the decision variables respectively.

3.2.3 Constraints

Constraints in LP model are used to limit the values of the decision variables. They typically represent limiting values of the resources used in the problem. In our study constraints can be applied to average loss rate, buffer delay, average power consumption etc. The general form of constraints can be

$$\sum_{i \in N} x_i \times a_{ij} \leq b_j \tag{3.3}$$

where $j \in 1....m$ represents the m constraints, a_{ij} represents the coefficient of constraint j on decision variable i and b_j represent the limit on constraint j.

Besides these resource constraints there are also constraint on decision variable. Since most of the LP models represents real life systems, decision variables are required to have positive values. Also in most of the cases the decision variables usually represent a probability values of choosing a particular action in various states of the system, so another default constraint on decision variable requires the sum of decision variable values to be equal to one.

$$\sum_{i \in N} x_i > 0 \tag{3.4}$$

$$\sum_{i \in N} x_i = 1 \tag{3.5}$$

3.2.4 General Linear Programming Problem

A general LP problem can be summarized as

$$\max / \min \sum_{i \in N} x_i \times R_i \tag{3.6}$$

$$\sum_{i \in N} x_i a_{ij} \leq b_j \quad \forall \; j \in N \tag{3.7}$$

$$\sum_{i \in N} x_i > 0 \tag{3.8}$$

$$\sum_{i \in N} x_i = 1 \tag{3.9}$$

A LP formulation thus consists of the following elements:

1. Identifying the decision variables,
2. Defining the objective function,
3. Formulating the constraint variables and there limits and
4. Ensuring default limits on decision variables

3.2.5 Linear Programming Formulation for Markov Decision Processes

The formulation of MDP using LP model relies on dynamic programming approach. The exact proof of formulation of constrained MDP problem as a LP model is beyond the scope of this work. The breif process of converting the MDP model with average reward criteria for optimization to approximate LP model is explained below.

Let π_s indicate the stationary distribution of state $s \in S$ of system, then the expected average reward criteria v for the system in all states can be defined as

$$v = \sum_{s \in S} \pi_s r(s) \tag{3.10}$$

$r(s)$ represents the expected reward seen by the system whenever it visits the state s and be defined as

$$r(s) = \sum_{a \in A} h(s,a) r(s,a) \tag{3.11}$$

Here $r(s,a)$ represents the reward for performing action a in state s and $h(s,a)$ indicates a randomize policy representing the probability that an action a is chosen in state s of the system. The objective function of the linear program can thus be represented as

$$max/min \quad \sum_{s \in S} \sum_{a \in A} \pi_s h(s,a) r(s,a) \tag{3.12}$$

The decision variable thus can defined as

$$x(s,a) = \pi_s h(s,a) \tag{3.13}$$

The remaining default constraints on linear program that ensures the average criteria and minimum value of decision variables can thus be written as

$$\sum_{a \in A} x(j,a) - \sum_{i \in S'} \sum_{a \in A} p_{ij} x(i,a) \qquad j \in S \tag{3.14}$$

$$\sum_{s \in S} \sum_{a \in A} x(s,a) = 1 \tag{3.15}$$

$$x(s,a) \geq 0, \qquad \forall s, \forall a \tag{3.16}$$

The first constraint provides the approximation of the bellman's equation in LP approximation which ensures that the value found must use the average reward criteria and be optimal. The second constraint provides the default constraint on the decision variable that it's sum must be equal to one since its a probability distribution. The last constraint ensures that the decision variables take non-negative values.

The various resource constraints can be provided to the LP formulation by

$$\textstyle\sum_{s \in S} \sum_{a \in A} x(s,a) \times C(s,a) \leq C_O \tag{3.17}$$

$C(s,a)$ represents the value of constraint variable for system state s and action a while C_O gives the limit on the constraint variable. Once the system model is complete, the parameters are passed to the LP Solver to get the value of the decision variable $x(s, a)$. In order to obtain the policy from the decision variable matrix we select the action in each state that has the maximum probability. States having same decision variable values for all actions can take any action possible.

3.2.6 Solving LP Model in Matlab

MATLAB [8] has a tool box for solving the MDP models. The general form of LP solver in MATLAB is represented as

$$x = linprog(f, A, b, Aeq, beq, lb, ub) \tag{3.18}$$

The *linprog* function solves $min \quad f' * x$ problem such that $A * x \leq b$. Where f represents the reward function, x represents the decision variable, A represents the inequality value matrix for the constraint variable and b represents the limits on the inequality constraints while Aeq and beq represents the equivalent equality constraints respectively. lb and ub provide the lower and upper bounds on the decision variable x. Based on these parameters the system is solved and decision variable values are obtained which are then used to find the optimal policy.

3.3 Summary

This chapter provides basic background into MDP and LP formulation. The formulation of MDP consists of identifying the system states, transition probability matrices, set of actions and reward functions to optimize. Similarly the formulation of LP problem consists of identifying the objective function, the decision variables, setting up the constraints and the providing default decision variable constraints.

CHAPTER 4

SYSTEM MODEL

QoS in biosensor networks requires a careful management of the resources under strict and average constraints. In applications that require a high response time, the average buffer delay should be kept within a bound to ensure a certain level of QoS. Similarly, tasks that need a large number of samples require a high system throughput to ensure enough data is available when making decisions. Losses at the inputs of buffers can also affect the performance of biosensor networks. Since biosensor networks have limited supply of energy and can cause heating of the tissues surrounding them, controlling the power consumption is another significant QoS constraint. In this thesis work, our objective is to optimize the average sample transmissions and average power consumption while putting constraints on the remaining QoS parameters like average loss rate and average delay etc.

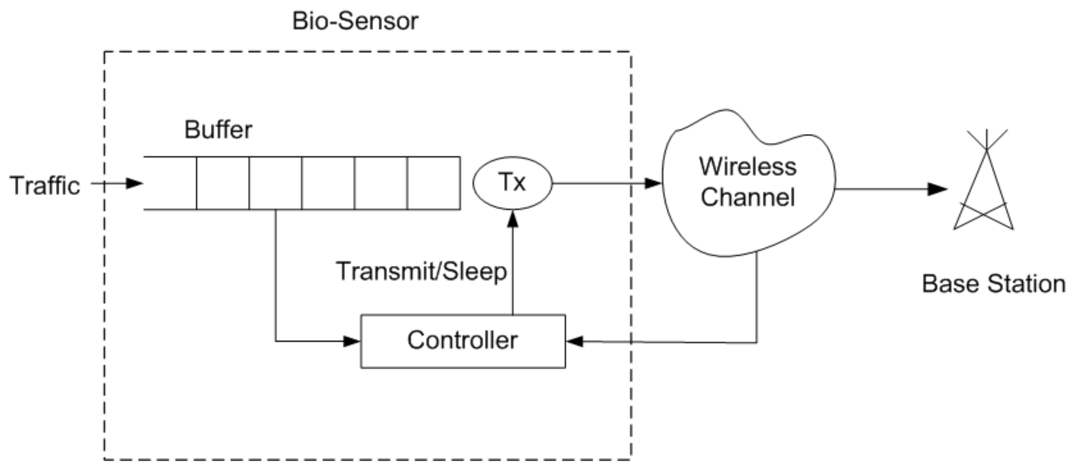

Figure 4.1: System model for a biosensor node

4.1 Physical Model

The biosensor network is assumed to be a decentralized system such that each biosensor has its own system state information based on which the optimal policy is determined. Biosensors communicate over a correlated fading channel that connects them to a BS. Each biosensor node has a limited size buffer. Fig. 4.1 shows the internal structure of a biosensor node in this network. The traffic at the input of the buffer represents the samples generated by the biosensing elements. These arriving samples experience delay and loss while travelling through the biosensor node. We assume that the current CSI and buffer state is known by the biosensor. The controller, based on the state of biosensor, is responsible for determining an efficient policy that optimizes certain QoS parameters. In each time slot, based on the decision by the controller, the transmitter either sends the required number of samples through the wireless channel to the base station or remains asleep. In this thesis we discuss the trade-off between various QoS parameters like average transmissions rate, loss rate, delay and power consumption. This is accomplished by varying different system parameters and studying their effect on the thermal state of the biosensor.

4.2 Mathematical Model

For mathematical modeling of the system, the channel is assumed to be slowly varying Rayleigh fading channel that can be modeled as a FSMC [38]. FSMC models accurately depict the correlation between different channel states for block level user communication. We assume that the time is slotted and each time slot is further partitioned into F channel uses. The incoming traffic is assumed to be Poisson distributed with average arrival rate λ. In order to study the temperature effects on biosensor networks and the corresponding impact on the QoS, we present two mathematical formulations. The two models differ in how they capture the temperature variations in the system.

4.2.1 Average Thermal Increment Model

In this system model, the temperature variations are analysed by constricting average thermal increment of the biosensor network. A thermal increment corresponds to an abstract temperature increase caused by the energy used to transmit a symbol during a channel use within a time slot. The temperature variations are not part of the system state. Only the average thermal constraint is included while calculating optimal policies. The state of the system is characterized by two variables;i.e., the current state of the buffer and current channel state. This helps in reducing the state space of the system and utilizes less resources while computing the optimal policies. Since the thermal state of the biosensor is not included as a state variable, the biosensor node is bound to eventually reach the temperature threshold after certain period of time.

4.2.2 Strict Temperature State Model

In this model the temperature changes of the biosensor node are included as part of the system state. This puts a strict limitation on the allowed temperature variations. A minimum and maximum range of temperature levels is defined and the temperature states as part of the system states are chosen accordingly. The system states in this model consists of the current temperature level, channel state and buffer state. This model provide a strict constraint on the temperature but has the disadvantage of increased number of system states which can affect the performance if the computational resources are limited.

Both the models differ only in how temperature is captured into the model. The previous model handled the temperature variations by constricting the average thermal increment as a constraint in the biosensor network. In this model the states of the system are characterized by three variables;i.e., current temperature, current buffer state and current channel state. The process of capturing the temperature as a state variable is discussed later. In the next few sections we represent mathematical models for channel state, buffer states and sample transmissions which are common to both the cases.

4.2.3 Channel State Model

We consider a slotted Rayleigh fading channel with Additive White Gaussian Noise (AWGN) N_o and channel bandwidth W. The Rayleigh faded channel is assumed to be slowly varying so that the received Signal to Noise Ratio (SNR) remains within a certain limit during a single slot and transitions are only allowed to current or adjacent states. This slowly varying discrete time Rayleigh fading process can be represented by a FSMC having K channel states [39]. The channel states are numbered from 0 to $K-1$. The channel gain for each state c, $c \in (0, ..., K-1)$, is represented by θ_c. The channel state transition probability during time slot i is given by

$$P_C(c, c') = P[C_i = c' | C_i - 1 = c] \tag{4.1}$$

$P_C(c, c')$ can be calculated by partitioning the range of channel gains into finite number of intervals and using the fading process information given in [40]. We assume that the channel state transition probabilities for all channel states are available(e.g, see [11]).

4.2.4 Buffer State Model

Data measured by sensing elements arrive at the input of a finite buffer of size B_{size}. Let σ_t indicate the number of arrivals at the input of buffer between time slot $t-1$ and t. The samples arriving in current time slot can be transmitted at least in the next time slot [41]. The arrivals are assumed to be Poisson distributed and independent of the channel fading and noise process[42]. Let the average arrival rate be $\lambda = E[\sigma_t]$. We consider a truncated Poisson distribution which can be calculated as follows.

$$p^a(\sigma_t = i) = e^{-\lambda}\frac{\lambda^i}{i!}, \qquad i = \{0, 1, ..., Z-1\} \tag{4.2}$$

$$p^a(\sigma_t = Z) = 1 - \sum_{i=0}^{Z-1} p^a(i) \tag{4.3}$$

Where Z indicates the maximum number of incoming samples. The controller of the biosensor node is responsible for determining the optimal action to take based on the current state of the wireless channel and number of samples in the buffer.

Let $B = B_0, B_1, ..., B_{size}$ denotes the state space of the buffer that is of size B_{size}. The number of samples in the buffer at time slot $t+1$ can be calculated by

$$B_{t+1} = \min\{B_t - A_t + \sigma_{t+1}, B_{size}\} \tag{4.4}$$

Based on the average arrival rate, the value of Z, action taken in current time slot and current buffer state, we can calculate the transition probability matrix of changes in the buffer states corresponding to the actions performed from Eq.(4.2).

4.2.5 Transmission Model

The transmitter is responsible for taking certain number of samples from the buffer and transmit them over the correlated faded channel. Let $A = a^0, a^1, a^2, ..., a^A$ indicate the set of actions performed by the transmitter where a^1 indicates one sample is transmitted , a^2 indicates two samples are transmitted and so on. a^0

represents the sleep action;i.e., no sample is transmitted by the biosensor node in this state.

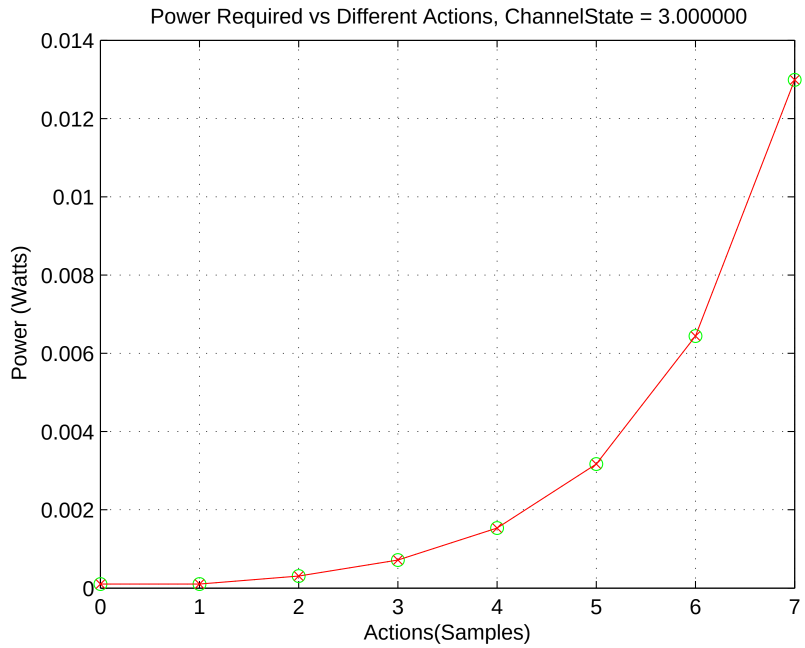

Figure 4.2: Change in transmission power for different actions for the same channel state ($c = 3$)

- **Transmission Power**

Let $P(C_k, a^j)$ indicate the power required to take action j when the channel state is k. Power required to take a certain action in slot t must belong to $P_t(c, a) \in P_{op}$, where P_{op} indicates the set of power levels supported by the transmitter. Furthermore, we enforce a fixed Bit Error Rate (BER) constraint on all the transmissions done by the transmitter. Assuming an adaptive M-ary Quadrature Amplitude Modulation (MQAM) modulation scheme with ideal coherent phase detection, the power required to satisfy a particular BER can be evaluated by using the

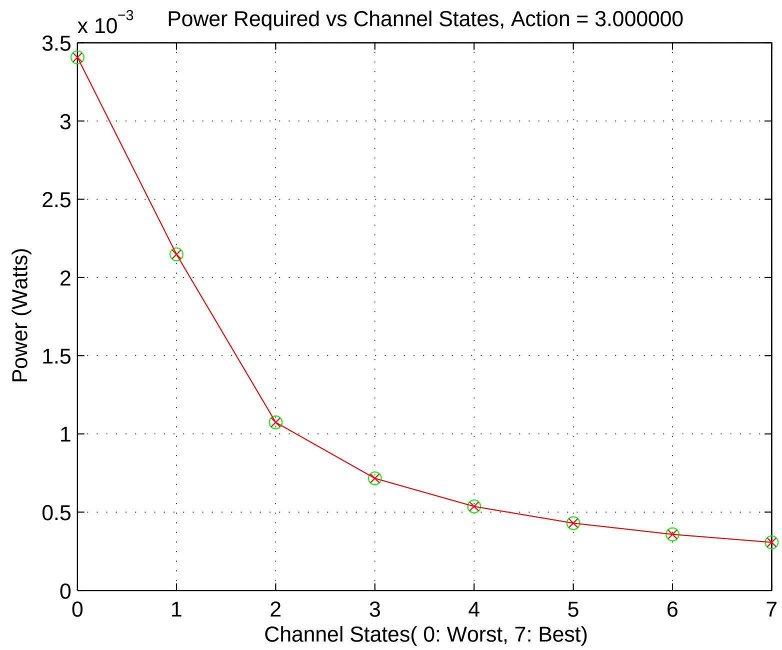

Figure 4.3: As channel state improves, less transmission power is needed for the same action (a^3)

equation from [11].

$$P(c, a) \geq \frac{W.N_O}{\theta_c}.(\frac{-(2^{a-1})\log(5.E_b)}{1.5}) \tag{4.5}$$

In (4.4) N_O represents the channel noise, E_b represents the fixed BER constraint that is satisfied assuming coherent phase detection, θ_c represents the channel gain when the channel state is c and W represents the bandwidth of wireless transmission. If the required power is less than that described in (4.4) , it means that action is not feasible. Power calculated in (4.4) give a pessimistic estimate of the power required to achieve a certain BER for different channel states and actions. The plot for variations in transmission power for varying system states is plotted in Fig. 4.2 and Fig. 4.3. It can be seen in Fig. 4.2 that the transmission power increases as the number of samples required for transmission increases. Fig. 4.3 shows the effect of changing the channel states on the transmission power requirement. As the channel gain improves and thus as we move from worst to best channel state, the transmission power required decreases.

- **Transmission Rate**

The rate of transmission for F channel uses in each time slot can be calculated as In each time-slot the biosensor node's rate of transmission can be calculated by

$$Rate = \frac{G.\Phi(A_t)}{F} \tag{4.6}$$

Where Φ represents the number of bits per symbol used for transmission of A_t samples during the next F channel uses. G represents the size of incoming samples in terms of bits. If we set $G = F$, rate can be computed as equal to Φ. We can transmit different number of samples by changing the number of bits per symbol. If we set number of bits per symbol equal to number of samples transmitted in a time slot, then $\Phi(A_t) = A_t$;i.e., the transmission rate becomes equal to the action suggested by the optimal policy.

$$Rate = A_t \tag{4.7}$$

4.2.6 General MDP Formulation

The formulation of the system as a MDP requires the system states, the possible actions, system state transition probabilities for all possible actions, and the cost function. Then, based on the current state of the system, possible actions and cost of each action, a certain objective is maximized.

- **System States for Average Thermal Increment Model**

In this model, we formulate the problem as an average cost MDP having system state space S given by

$$S = B \times C = s_1, s_2, ..., s_Q \tag{4.8}$$

where

$$Q = B_{size} \times K$$

So the total number of system states is equal to the size of buffer states space times the size of channel states space. Each of the system state consists of channel state information and buffer states information.

$$s_i = (b_i, c_i) \quad i \in \{1, 2, ...Q\} \tag{4.9}$$

- **System States for Strict Temperature Model**

In this model, the problem is formulated as an average cost MDP having system state space S given by (4.9)

$$S^v = B \times C \times T = s_1^v, s_2^v, ..., s_{Q'}^v \tag{4.10}$$

where

$$Q' = B_{size} \times K \times T_{size}$$

So the total number of system states is equal to the size of buffer states space times the size of channel states space times the temperature states space. Each of the system state consists of channel state information, current temperature state information and buffer states information.

$$s_i^v = (b_i, c_i, t_i) \quad i \in \{1, 2, ...Q'\} \tag{4.11}$$

- **Transition Probabilities for Average Thermal Increment Model**

State transition probabilities describe how the system transitions from one state to another. Since the system state depends on buffer state and state of the wireless channel which are independent, the state transition probability of the system can be calculated by simple multiplication of the transition probabilities of channel and buffer states.

$$P_S[s'|s,a] = P_C[c'|c] \times P_B[b'|b,a] \tag{4.12}$$

Where s, c and b represent the current state of the system, wireless channel and buffer respectively. On the other hand, s', c' and b' represent the next state of the system, wireless channel and buffer when action a is performed.

- **Transition Probabilities for Strict Temperature Model**

In the second formulation, the system states consist of current temperature alongside buffer and channel states. Since in this work we assume that the temperature variations are not random and are caused by the action chosen in each of the system state, the transition probability matrix of the system is thus independent of the temperature state of the system.

$$P_S^v[s^{v'}|s^v,a] = P_C[c'|c] \times P_B[b'|b,a] \tag{4.13}$$

s^v, c and b represent the current state of the system, wireless channel and buffer respectively. Whereas $s^{v'}$, c' and b' represent the next state of the system, wireless channel and buffer when action a is performed.

- **Actions**

Action in each system state corresponds to transmission of certain number of samples. The transmission in turns depends on the power required to take a particular action. So the transmission model proposed in previous section can be used here to represent the actions taken. The action state space consists of A actions with 0 indicating the sleep action;i.e., no transmission, 1 representing transmission of one sample, up to A representing transmission of A samples.

- **Policies**

Let μ denote the set of all policies which describe certain action to take in every state of the system $\mu = \pi_1, \pi_2, ...\pi_i, ...$ having state space $S \times A$. Each of the policies corresponds to a sequence of actions taken in each system state. Our goal is to find optimal policies π^* for various QoS goals. The cost function depends on the QoS parameter we want to control. These QoS parameters are discussed in next section.

- **Average Transmission Power Optimization**

Transmission power is one of the major causes of heat that effect the tissues surrounding the biosensor node. The RF waves generated by each transmission increases the surrounding temperature of the biosensor node. So keeping the average power consumption within certain bounds can certainly improve the battery life of a biosensor node and thermal state of the subject in which they are present. So when seeking optimal policies, minimization of average power consumption can play an important role in improving the performance of a biosensor network. The expected long term average transmission power while following a certain policy can be calculated as.

$$P_{Avg}(\pi) = \lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [P(c_i, \pi(a_i, c_i))] \tag{4.14}$$

where $\pi(a_i, c_i)$ represents the action suggested by policy π while P represents the transmission power shown in (4.4).

- **Average Transmission Rate Optimization**

The transmission rate in a biosensor network plays an important role in improving the robustness of the system. The disadvantage, however, of successive transmissions is the increase in temperature of the surrounding tissues. The idea of proposing two separate mathematical models is based on the fact that how they handle the optimization of average sample transmissions. The thermal model tackles the increase in temperature caused by these transmissions using average thermal increment constraint while the strict temperature model handles the issue by introducing the temperature as a system state. The expected long term average transmission rate while following a certain policy can be calculated as.

$$R_{Avg}(\pi) = \lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [R(s_i, \pi(a_i, s_i))] \tag{4.15}$$

where $\pi(a_i, s_i)$ represents the action suggested following policy π while R represents the reward for transmission rate.

The transmission rate in (4.6), however, doesn't take into consideration the loss rate at the input of the buffer. So the reward for average transmission rate optimization can be represented as

$$R = A_t - L_t \tag{4.16}$$

where L_t represents the loss rate at input of buffer which is discussed next.

4.2.7 QoS Metrics

Different QoS metrics are controlled in such a way that the service requirements for objective functions in both the mathematical formulations are optimized. These QoS constraints are discussed next.

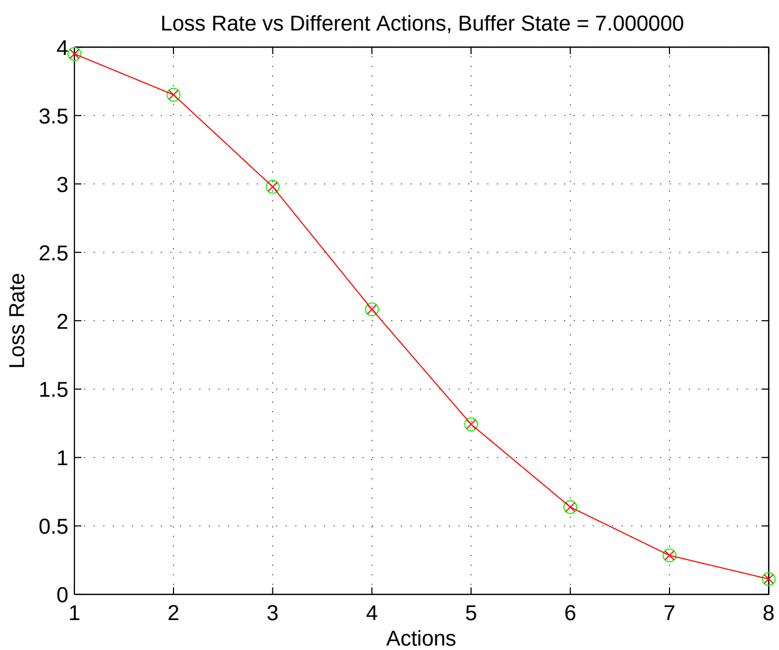

Figure 4.4: Effect of increasing sample transmission on loss rate with fixed average arrivals ($\lambda = 3$) and channel state ($c = 3$)

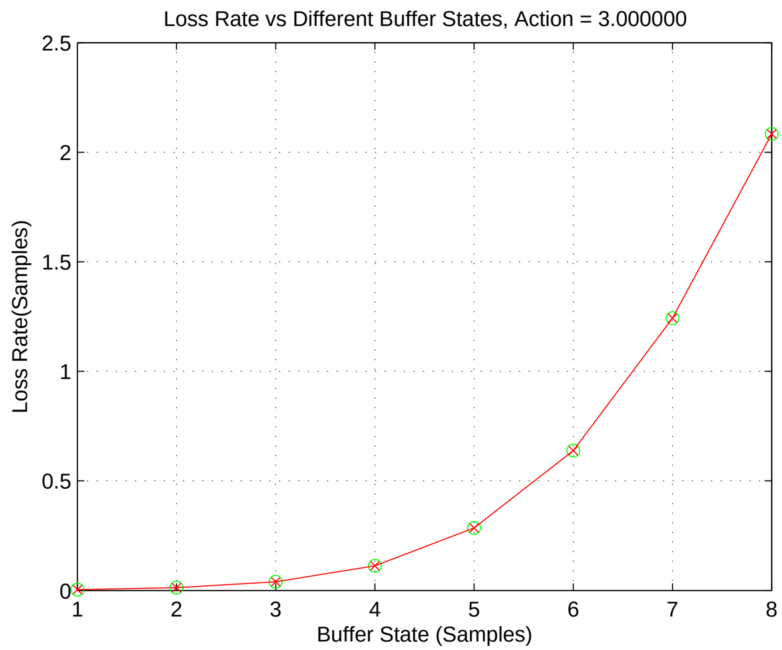

Figure 4.5: Loss rate increases as buffer occupancy increases for a fixed average arrivals ($\lambda = 3$) and action ($a = 3$)

- **Average Loss Rate**

Average loss rate represents the expected number of samples that are dropped due to buffer overflow. Loss rate at the buffer input is itself a random variable which is dependent on the arrivals, current state of the buffer and action taken in a certain time slot t.

$$L_t(s,a) = \max\left\{b_t + \sigma_t - a_t - B_{size}, 0\right\} \tag{4.17}$$

In (4.13) σ_t represents the number of arrivals at input of buffer at time slot t which are calculated using (4.2) with maximum arrivals Z, b_t represent buffer state at time slot t, a_t represents the action taken at time t and B_{size} represents the buffer capacity. The variations in loss rate with changing actions and buffer states are plotted in Fig. 4.4 and Fig. 4.5 respectively. It can be seen that increase in number of sample transmission causes a decrease in the loss rate while increase in number of samples in the buffer causes a rise in the loss rate at buffer input of biosensor node. Finally, the average loss rate L can evaluated by calculating the first moment of (4.16);i.e.,

$$L_{Avg}(s,a) = E(L_t(s,a)) \tag{4.18}$$

- **Average Delay**

Average sample delay represents the delay experienced by the samples when they arrive at the input of the buffer. Buffer delay at time slot $t+1$ is related to the buffer occupancy by Little's theorem as

$$d_{t+1}(b,a) = \frac{1}{\lambda}E[b_t] \tag{4.19}$$

Thus the instantaneous buffer delay can be calculated as

$$D_{t+1}(b,a) = \frac{b_t}{\lambda} \tag{4.20}$$

And the long term average delay for following a certain policy $i \in \pi$ is calculated by

$$D_{Avg}(\pi) = \lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [D(b_i, \pi(a_i, b_i))] \tag{4.21}$$

- **Average Thermal Increment**

Another important QoS constraint required to keep the temperature changes of the system in check during average throughput maximization is the average temperature change. The actual values of temperature variations are quite small which can be calculated by Pennes bioheat equation[36] and FDTD [37] method. For simplicity and abstraction we define average thermal increase as a QoS parameter. A thermal increment state represents the abstract increase in temperature caused by energy utilization of a symbol during channel uses within each time slot. Abstractly, this constraint represents the average increase in thermal state of the system during each channel use.

In the proposed model, each action $a \in 1\ to\ M$ increases the thermal state of the system by equivalent amount e.g. transmission of one sample increase the thermal state of the system by one unit. The thermal increase also depends on the state of the channel K with 0 being the worse channel state and $K-1$ being the best channel state. Transmission in worst channel state adds further units of thermal increase to the equation proposed in (4.21). The first case in (4.21) indicates the sleep action which causes the thermal state of the system to decrease by one unit. The long term average thermal increment for following a certain policy π can thus be evaluated in (4.22).

$$T_{t+1}(s,a) = \begin{cases} -1 & a \in a^0 \\ \\ a_t + K - c_t - 1 & a \in a^1, a^2, ...a^A \end{cases} \tag{4.22}$$

$$T_{Avg}(\pi) = \lim_{n \to \infty} \frac{1}{n} E \sum_{i=1}^{n} [T(s_i, \pi(a_i, s_i))] \tag{4.23}$$

4.2.8 Constrained MDP Formulation for Average Temperature Increment Model

In this section we formalize the problem as a constrained MDP where a particular objective function is optimized while putting various constraints on other QoS parameters . The first MDP formulation maximizes the system transmission rate while keeping the average power, delay, thermal increment and loss rate within bounds. The second MDP formulation optimizes the system power consumption while keeping a minimum Transmission rate constraint alongside QoS constraints and keeps the biosensor network in safe operating zone.

- **Average Transmission Power for Thermal Increment Model**

Minimizing the system average transmission power has the benefit of minimizing the thermal increment as well. So in this optimization there is no need to explicitly introduce the average thermal increment as a constraint since the average transmission power minimization automatically handles that. Thus, our objective function in described as

$$\min_{\pi} J_p(\pi) = \lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [P(s_i, \pi(a_i, s_i))] \tag{4.24}$$

Constrained to :

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [R(s_i, \pi(a_i, s_i))] \geq R_O \tag{4.25}$$

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [L(s_i, \pi(a_i, s_i))] \leq L_O \tag{4.26}$$

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [D(s_i, \pi(a_i, s_i))] \leq D_O \tag{4.27}$$

where $\pi(a_i, s_i)$ represents the action suggested by policy i in system state s_i where $s_i = (b_i, c_i) \quad i \in \{1.....Q\}$. L_O and D_O define the limits on average loss rate and average delay while the first constraint defines the minimum average transmission rate objective the system is required to maintain.

- **Maximizing Average Transmission Rate for Average Thermal Increment Model**

Increasing the transmission rate causes an increase in the system temperature. In average temperature increment model we handle the increase in temperature by putting a constraint on the average thermal increment which is defined previously in (4.22). Besides the regular QoS metrics, average power consumption is also constrained to make sure that the system utilization doesn't exceed the threshold.

The objective in this case along with the constraints is now defined as

$$\min_{\pi} J_p(\pi) = \lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [R(s_i, \pi(a_i, s_i))] \tag{4.28}$$

Constrained to :

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [P(s_i, \pi(a_i, s_i))] \leq P_O \tag{4.29}$$

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [L(s_i, \pi(a_i, s_i))] \leq L_O \tag{4.30}$$

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [D(s_i, \pi(a_i, s_i))] \leq D_O \tag{4.31}$$

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [T(s_i, \pi(a_i, s_i))] \leq T_O \tag{4.32}$$

where $\pi(a_i, s_i)$ represents the action suggested by policy i in system state s_i where $s_i = (b_i, c_i), \quad i \in \{1.....Q\}$. On the other hand, L_O, P_O, T_O and D_O define the limits on average loss rate, transmission power, thermal increment and delay respectively.

4.2.9 Constrained MDP Formulation for Strict Temperature Model

The objective of minimizing average transmission power while keeping the system is achieved in thermal increment state model. However, in average transmission rate maximization, although we are able to partially control the increase in temperature by constricting the average thermal increment, the system will eventually cross the temperature threshold after some time. In order to handle this issue we for average transmission rate maximization strict temperature model is used. We don't use this for average transmission power minimization because that objective already handles the temperature increase accurately, so there is no need to add an extra state variable and increase the load on resources.

- **Maximizing Average Transmission Rate for Strict Temperature Model**

For strict temperature model we handle the increase in temperature by including temperature as a state variable in the system. The state variable has a strict minimum and maximum range which limits the temperature increase. Besides the regular QoS constraints, average power consumption is also constrained to make sure that the system utilization doesn't exceed the threshold. We can further control the temperature increase within the strict temperature range by using the average temperature constraint that works similar to the thermal increment constraint in previous model. The objective in this case along with the constraints is now defined as

$$\min_{\pi} J_p(\pi) = \lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [R(s_i^t, \pi(a_i, s_i^t))] \tag{4.33}$$

$Constrained\ to:$

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [P(s_i^v, \pi(a_i, s_i^v))] \leq P_O^v \tag{4.34}$$

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [L(s_i^v, \pi(a_i, s_i^v))] \leq L_O^v \tag{4.35}$$

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [D(s_i^v, \pi(a_i, s_i^v))] \leq D_O^v \tag{4.36}$$

$$\lim_{n\to\infty} \frac{1}{n} E \sum_{i=1}^{n} [T(s_i^v, \pi(a_i, s_i^v))] \leq T_O^v \tag{4.37}$$

where $\pi(a_i, s_i^v)$ represents the action suggested by policy i in system state s_i^v where $s_i^v = (b_i, c_i, t_i), \quad i \in \{1.....Q'\}$. On the other hand, L_O^v, P_O^v, T_O^v and D_O^v define the limits on average loss rate, transmission power, temperature and delay respectively..

4.2.10 LP Formulation for Thermal Increment Model

QoS provisioning in biosensor networks requires providing application specific optimal services while keeping other system parameters within bound. The model for biosensor network proposed in the previous section can be solved using different MDP algorithms like Value Iteration, Policy Iteration and Linear Programming. Since our problem is constrained MDP, the optimal policies obtained by solving the system proposed are random[43]. Linear programming techniques have significantly similar correspondence for solving constrained MDP. Also choosing linear programming techniques allow us to easily enforce multiple constraints to the system at once. Policies obtained by this method are feasible as long as the constrained MDP is feasible itself.

- **General LP Formulation**

Let $x(s, a)$ indicate the decision variable in solving the MDP models obtained in previous section. $x(s, a)$ represents the steady state probability distribution when the system is in state $(s = (b, c))$ and action a is performed. Based on different rewards and depending on the QoS parameters, we want to optimize $x(s, a)$ to obtain an optimal policy which describes what action to take when the system is in state s. The MDP model proposed is solved using LP techniques in MATLAB [8]to obtain optimal operating policies for correlated wireless channel. The default mode for LP solver is to minimize the reward function.

Since the problem is formulated as an average cost constrained MDP, there are certain basic constraints that must applied for each implementation.

$$\sum_{s \in S} \sum_{a \in A} x(s, a) = 1 \tag{4.38}$$

$$\sum_{a \in A} x(j, a) - \sum_{i \in S} \sum_{a \in A} p_{ij}(a) \times x(i, a) = 0 \quad j \in S \tag{4.39}$$

$$x(s, a) \geq 0 \quad \forall\, s \in S, \quad \forall\, a \in A \tag{4.40}$$

(4.37) ensures the $x(s, a)$ is an probability distribution with its sum over all system states $s \in S$ and actions $a \in A$ is equal to one. The second constraint in (4.38) ensures that we are solving an average cost constrained MDP and the third constraint (4.39) enforces that the decision variable $x(s, a)$ is always positive. These basic LP constraints are applicable to all the policies obtained in the next sections.

- **Maximizing Average Transmission Rate**

System throughput maximization is an important QoS guarantee requirement in applications requiring accurate and abundant data at base station to process. So the reward criteria for maximization of average transmission rate obtained in (4.14) can be translated into LP model as

$$\max x \sum_{s \in S} \sum_{a \in A} x(s,a) \times R(s,a) \tag{4.41}$$

subject to the following minimum QoS constraints:

$$\sum_{s \in S} \sum_{a \in A} x(s,a) \times P(s,a) \le P_O \tag{4.42}$$

$$\sum_{s \in S} \sum_{a \in A} x(s,a) \times L(s,a) \le L_O \tag{4.43}$$

$$\sum_{s \in S} \sum_{a \in A} x(s,a) \times T(s,a) \le T_h \tag{4.44}$$

$$\sum_{s \in S} \sum_{a \in A} x(s,a) \times D(s,a) \le D_O \tag{4.45}$$

Inequalities in (4.40) , (4.41), (4.42)and (4.43) provide the constraint that the average values of power consumption $P(s,a)$, loss rate $L(s,a)$, thermal increment $T(s,a)$and delay $D(s,a)$ do not exceed by a certain threshold P_O, L_O,T_h and D_O respectively. Since the default mode of LP solver used in MATLAB is to minimize. The reward matrix is multiplied by negative one to convert this into a maximization problem. The policy obtained by solving the LP model and the effects of changing the system parameters on the policy are discussed in the next chapter.

- **Minimizing Average Transmission Power**

The objective function obtained for minimization of average transmission power from (4.23) is translated into LP model and solved under remaining system constraints to obtain an optimal policy that minimizes the average transmission power of the system.

$$\min x \sum_{s \in S} \sum_{a \in A} x(s,a) \times P(s,a) \tag{4.46}$$

subject to the following minimum QoS constraints:

$$\sum_{s \in S} \sum_{a \in A} x(s,a) \times R(s,a) \geq R_O \tag{4.47}$$

$$\sum_{s \in S} \sum_{a \in A} x(s,a) \times L(s,a) \leq L_O \tag{4.48}$$

$$\sum_{s \in S} \sum_{a \in A} x(s,a) \times D(s,a) \leq D_O \tag{4.49}$$

Here (4.46)and (4.47) provide the constraint that the average values of loss rate $L(s,a)$ and delay $D(s,a)$ do not exceed by a certain threshold L_O and D_O respectively. The constraint in (4.45) ensures that there is a minimum average throughput requirement R_O satisfied by the policy. The LP solver excepts the constraints to be upper bounded. In order to lower bound the average throughput, the constraint in (4.45) is multiplied by negative one and passed to the LP solver.

4.2.11 LP Formulation for Strict Temperature Model

LP formulation for strict temperature model is similar to the thermal increment model. The system state s is replaced with s^v having temperature as part of the system state. Since we are only considering optimization of average transmission rate in this model, the LP formulation can be represented as

$$\max x \sum_{s \in S} \sum_{a \in A} x(s^v, a) \times R(s^v, a) \tag{4.50}$$

subject to the following minimum QoS constraints:

$$\sum_{s \in S} \sum_{a \in A} x(s^v, a) \times P(s^v, a) \leq P_O^v \tag{4.51}$$

$$\sum_{s \in S} \sum_{a \in A} x(s^v, a) \times L(s^v, a) \leq L_O^v \tag{4.52}$$

$$\sum_{s \in S} \sum_{a \in A} x(s^v, a) \times T(s^v, a) \leq T_h^v \tag{4.53}$$

$$\sum_{s \in S} \sum_{a \in A} x(s^v, a) \times D(s^v, a) \leq D_O^v \tag{4.54}$$

$x(s^v, a)$ represents the decision variable for the optimization of average transmission rate. P_O^v, L_O^v, T_h^v and D_O^v represents the thresholds on the average values of transmission power. loss rate, temperature and delay. The policy obtained by solving the LP model and the effects of changing the system parameters on the policy are discussed in the next chapter.

4.2.12 Computation of Optimal Policy

The LP solution computed for optimization of average transmission power and average transmission rate gives an optimal value of decision variable $x(s, a)$ which can be used in finding the optimal policy. The optimal policy for every state of the system is computed as follows

$$\pi^*(s, a) = \frac{x^*(s, a)}{\sum\limits_{i=1}^{A_s} x^*(s, a_i)} \quad \forall\, a \in A_s \quad and \quad s \in S \tag{4.55}$$

Here, A_s represents the set of feasible actions in each system state s. An optimal action in each state is chosen having maximum probability in the optimum decision variable matrix calculated through LP.

4.3 Summary

This chapter provides an detailed insight into the new model proposed for the biosensor network. Both physical and mathematical representations are given to support the viability of the model. We propose two different schemes for mathematical representation of the model based on the optimization requirements;i.e., thermal increment model and strict temperature model. The MDP framework is used to study the behaviour of the proposed mathematical models. As for solving the MDP models to obtain an optimal operating policy, we use LP formulation for constrained MDP. The implementation of the models developed and the results obtained are analysed and discussed in the next chapter.

CHAPTER 5

RESULTS AND DISCUSSION

In this chapter we solve the model proposed in the previous chapter to obtain the optimal policies and then simulate them. We analyse the effect of various QoS constraints on the optimal policies. Then, we study the different optimal policies obtained by solving the average thermal increment and strict temperature models. The thermal behaviour of the obtained policies is also discussed.

5.1 Configuration

Parameter	Value
G	$100\ bits$
B_{size}	$8\ Samples = 800\ bits$
K	8
T_{size}	4
A	8
λ	$3\ Samples$
W	$100\ MHz$
N_O	10^{-12}
f_D	$10\ Hz$
θ_{avg}	0.8

Table 5.1: Simulation parameters

Channel states c	0	1	2	3	4	5	6	7
θ_c	0	0.1068	0.2301	0.3760	0.5545	0.7847	1.1090	1.6636
$P_{c,c}$	0.9359	0.8552	0.8334	0.8306	0.8420	0.8665	0.9048	0.9639
$P_{c,c+1}$	.0641	.0807	.0859	.0835	.0745	.0590	.0361	0
$P_{c,c-1}$	0	.0641	.0807	.0859	.0835	.0745	.0590	.0361

Table 5.2: Channel states and transition probabilities

The following system parameters are used in the model formulation and simulation. Arrivals at the buffer input are assumed to be Poisson with an average arrival rate of three. Buffer size is set to eight samples. Eight channel states are considered. The state zero is assumed to be the worst with a very small gain. There are eight possible actions in each state of the system;i.e., transmitting from one up to seven samples or no transmission. Based on these system parameters, the MDP model is formulated as a linear program and solved using MATLAB. The slowly varying Rayleigh model is described in Table 5.2. It has an average power gain of 0.8 and a Doppler frequency of 10 Hz. Next, the effect of various parameters like arrival rate, delay and loss rate on the optimal policies is described.

5.2 Analysis and Insights

For the purpose of analysing the effect of various constraints on the optimization of average transmission rate and average power consumption, we vary the magnitude of the constraints on the average loss rate, delay and thermal increments to study their effects on the objective function. Values of the input parameters are also varied and their effects on both the constraints and objective function are studied.

5.2.1 Average Transmission Power

The objective function for the average transmission power provided in (4.45) is implemented in MATLAB with each constraint (i.e. (4.46), (4.47) and (4.48)) applied one at a time. The effect of each constraint on the average power consumption is studied.

- **Effect of Average Loss Rate**

The loss rate constraint provided in (4.47) is applied to the objective function in (4.45). The value of constraint L_O is varied. As a result, a new policy along with values for decision variables $x(s, a)$ are obtained which are applied to (4.45) to get the value of the average transmission power. The results are then plotted in Fig. 5.1. It can be seen that the average transmission power decreases as the average loss rate constraint increases. Since more samples are allowed to drop when the loss rate constraint is increased, the controller will use the least amount of power possible for transmission.

Next, the effect of changing the average arrival rate λ is studied. Fig. 5.1 shows the variations in average loss rate constraint and optimal average transmission power due to changing average arrival rates. It can be observed that increasing the arrival rate increases the average power consumption of the system. This is because there will be more samples in the buffer which need to be transmitted.

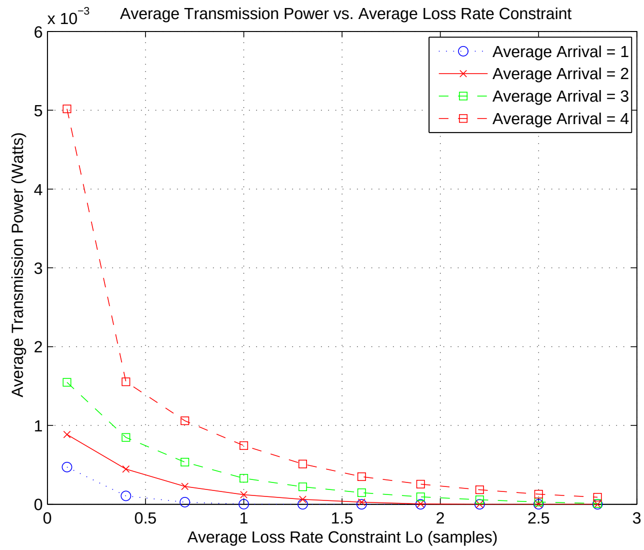

Figure 5.1: Reduction in the optimal average transmission power as the average loss rate constraint (L_O) is varied

- **Effect of Average Delay**

The delay constraint provided in (4.48) is applied separately to the objective function in (4.45). The value of the constraint D_O is varied and each time a new policy along with values for decision variables $x(s, a)$ are obtained. The optimal solution is applied to (4.45) to get the value of the optimal average power consumption. The results are then plotted in Fig. 5.2. It can be seen that the value of the optimal average transmission power decreases as the average delay constraint is increased. This indicates that as the constraint on average delay is increased, samples are allowed to experience more delays which results in lesser average power consumption.

Next, The effect of changing the average arrival rate λ is studied for average delay constraint. Fig. 5.2 shows the variations in average delay constraint and optimal average transmission power due to changing average arrival rates. The

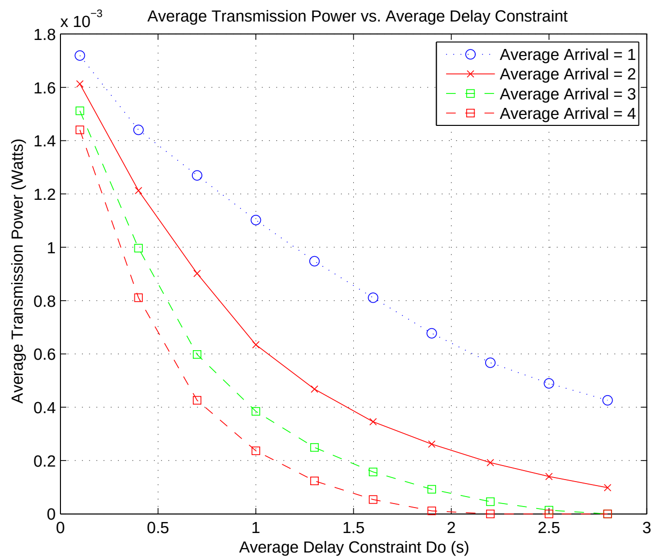

Figure 5.2: Optimal average transmission power reduces as the average delay constraint (D_O) increases

delay and average arrival rate are related inversely to each other (4.19). For example, for a fixed D_O, the left side of the delay constraint in (4.48) will be reduced if we increase the average arrival rate. This in turn should increase the optimal average power consumption to achieve the same delay constraint. However, the behaviour observed in Fig. 5.2 is the opposite. This can be explained by observing the Little's formulae in (4.19) which states that delay is also directly proportional to the buffer occupancy while inversely proportional to the average arrival rate. Also in (4.4), we can observe that the buffer occupancy is directly proportional to average arrival rate. So, based on the results obtained in Fig. 5.2, we can conclude that the effect of the increased delay dominates the reduction effect caused by increasing average arrivals which thus reduces the average power consumption.

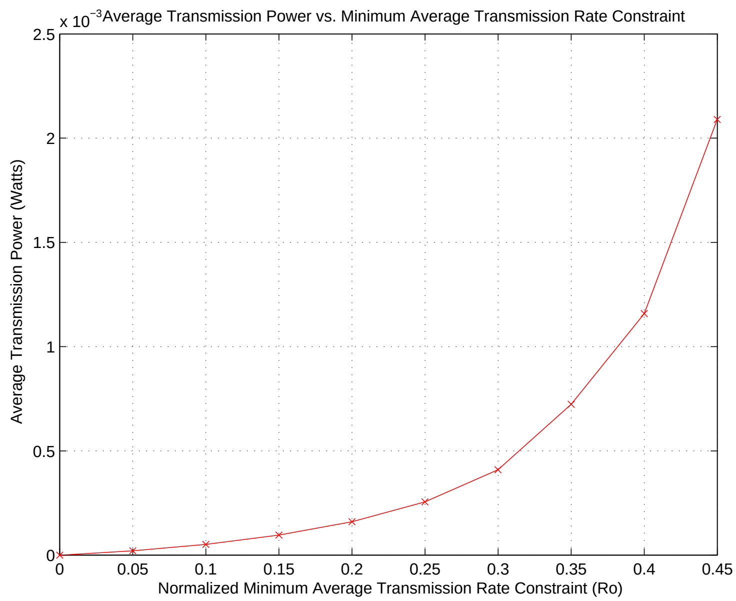

Figure 5.3: Increase in the minimum average transmission rate constraint (R_O) causes increase in the optimal average transmission power utilized

- **Effect of the Minimum Transmission Rate**

Now, the effect of having a minimum average transmission rate requirement on the optimization of average power consumption is studied. The behaviour obtained after applying the minimum average transmission rate constraint (4.46) is shown in Fig. 5.3. It can be seen that as the values of constraint increases, the optimal average power consumption increases. This happens because the increase in the minimum average transmission rate constraint requires the biosensor node to transmit more samples. As a result, the optimal values of average power consumption increases.

5.2.2 Average Transmission Rate

The objective function for average system transmission rate provided in (4.40) for thermal model is implemented in MATLAB with each constraint applied one at a time. The effect of each constraint on the average transmission rate is studied.

- **Effect of Average Power Consumption**

The average power constraint provided in (4.41) is applied to the objective function in (4.40). The value of constraint P_O is varied and each time a new policy along with values for decision variables $x(s, a)$ are obtained. These values are applied in (4.40) to get the value of the optimal average transmission rate. The results are then plotted in Fig. 5.4. It can be seen that the optimal average transmission rate increases as the average transmission power P_O increases. This indicates that as the constraint on average power is increased, more power is available which can be used to transmit increased number of samples which results in high average transmission rates.

The effect of increasing the arrival rate on average transmission rate is depicted in Fig. 5.4. It can be seen that as the average arrival rate increases the average transmission rate decreases. This is due to the fact that increase in average arrival rate cause an increase in loss rate which reduces the average transmission rate of the biosensor network.

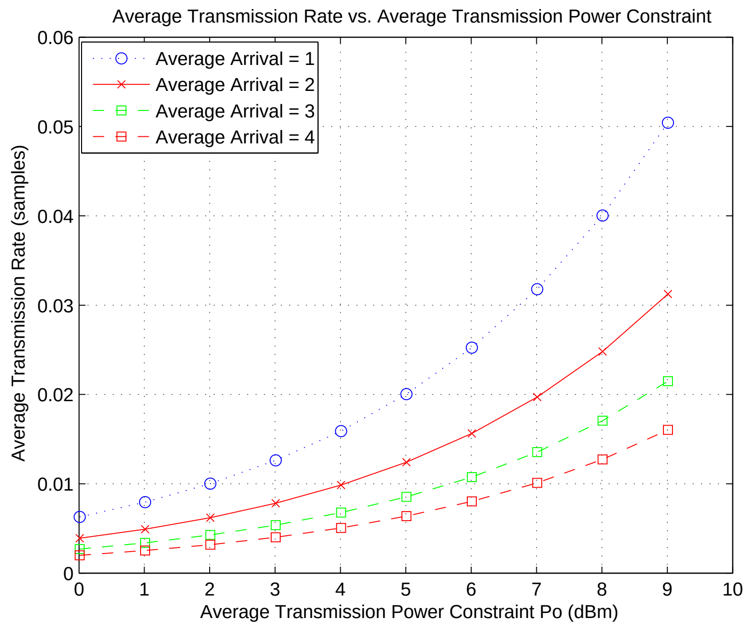

Figure 5.4: Effect of increasing the average arrival rate (λ) on the optimal average transmission Rate as the average power constraint (P_O) increases

- **Effect of Average Thermal Increment**

As will be discussed when simulating the optimal policies, average transmission rate maximization can cause the temperature of the system to increase by a large amount and this can effect the tissues of the subject. The average transmission power minimization objective indirectly minimizes the systems thermal state increase by minimizing the power consumption. However, for the average transmission rate maximization objective we need to explicitly include a constraint that controls the increase in the thermal state of the system at symbol level. The constraint on thermal increment provided in (4.43) is applied to the objective in (4.40). The value of the constraint T_h is varied to obtain various optimal policies, the results of which are used to calculate the optimal average transmission rate. Fig. 5.5 shows that the average transmission rate increases as the average thermal

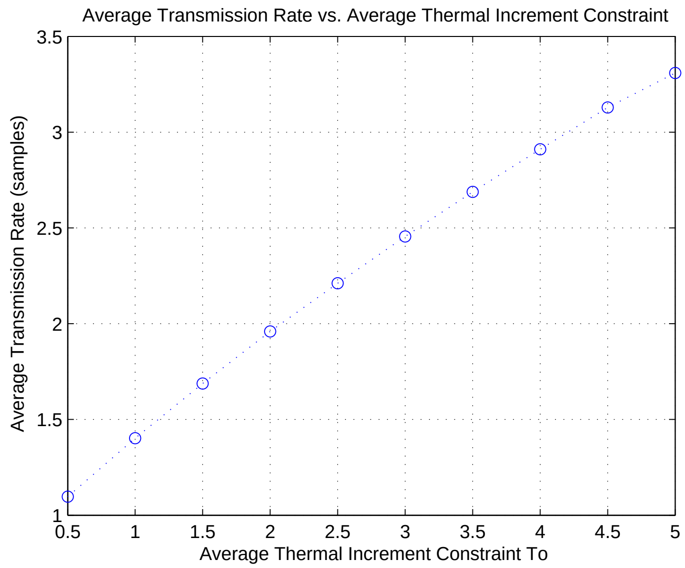

Figure 5.5: Increase in optimal average transmission rate as average thermal increment (T_h) increases

increment increases at the cost of damaging the tissues. So, we should try to keep the thermal increase constraint as small as possible for practical implementations for the average transmission rate maximization.

- **Effect of Average Delay**

Change in the average delay constraint does not effect the average transmission rate. The reason for such behaviour is that the delay depends on the buffer state and the average arrival rate. If we keep the average arrival rate constant the delay becomes directly related to the state of the buffer. But changes in the buffer state also cause similar changes in the transmission rate, as a result, the optimal average transmission rate remains constant for varying average delay constraint. However, if we increase the arrivals at the input of the buffer, the average loss rate and the delay increases which cause a reduction in the optimal average transmission as

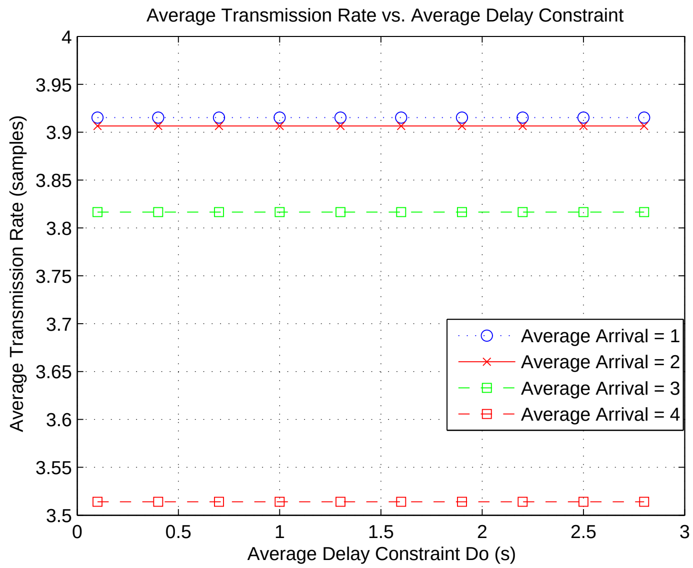

Figure 5.6: The average transmission rate remains constant for increasing average delay constraint (D_O) but decreases as the average arrival rate (λ) increases

depicted by Fig. 5.6

5.3 Optimal Policies for the Thermal Increment Model

In this section, we discuss the behaviour of the optimal policies obtained by solving the LP model proposed in the previous chapter. We provide the optimal policies for the thermal increment model and study how the thermal increment constraint affect the optimal policies. The effect of the strict temperature constraint to control the temperature increase is discussed in the next section.

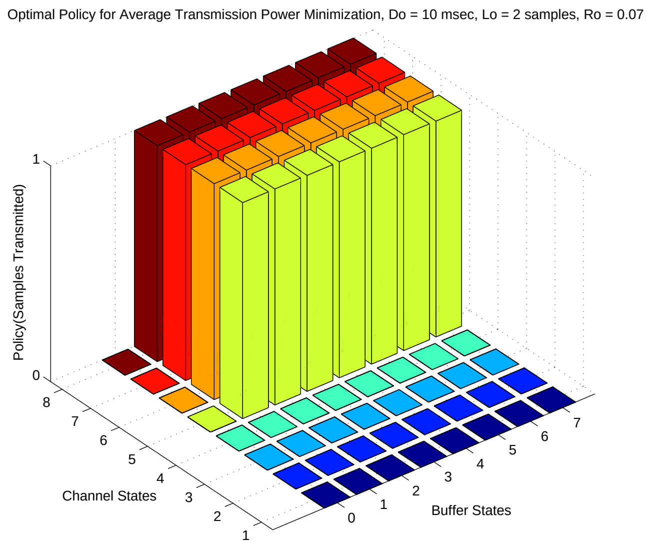

Figure 5.7: Optimal policy for minimizing average power consumption with $R_O = 0.07$, $D_O = 10\,msec$ and $L_O = 2\,Samples$

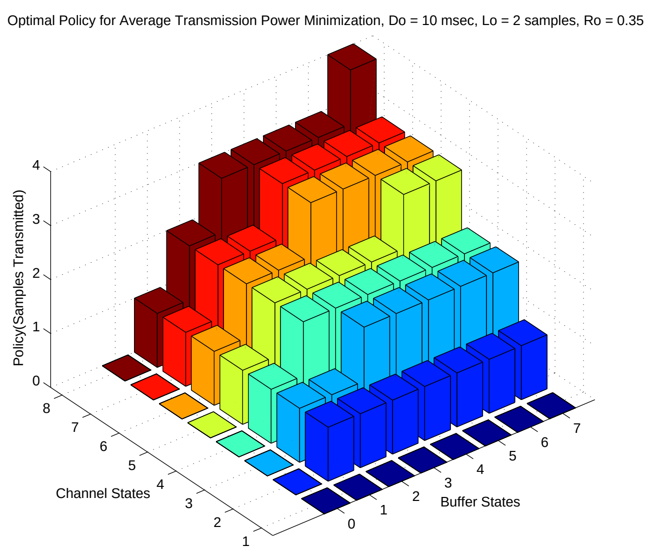

Figure 5.8: Increase in the minimum average transmission rate constraint ($R_O = 0.35$) results in increased number of samples transmissions in the optimal policy for average power minimization

5.3.1 Average Transmission Power Minimization

The optimal policy that results from solving the LP model in (4.45) - (4.48) is plotted in Fig. 5.7. The minimum average transmission rate constraint R_O is set to 0.07, average delay constraint D_O is set to $10\,msec$ and average loss rate constraint L_O is set to $2\,Samples$. The 3-D plot indicates that as the channel state improves from worst to better the policy suggest to transmit samples. Similarly, increased number of samples in the buffer also indicates that the transmitter should start sending more samples to the base station. However, since the objective here is to minimize the average power consumption and minimum average transmission rate constraint is quite small, maximum of one sample is transmitted even in the best channel case. This has the advantage of reducing the temperature increase of the biosensor node. However, if we increase the minimum average transmission constraint to 0.35, it can be seen in Fig. 5.8 that the number of samples transmitted as the buffer state improves is increasing.

5.3.2 Average Transmission Rate Maximization

The model proposed in (4.40) is solved using the constraints given in (4.41) - (4.44) and the obtained policy is plotted in Fig. 5.9. The average power constraint P_O is set to $2\,dBm$, average delay constraintD_O is set to $100\,msec$ and average loss rate constraint L_O is set to 2 $Samples$. No thermal constraint is applied to the policy obtained. The 3-D plot indicates once again that as the channel state improves from worst to better the policy transmits more samples. Similarly,

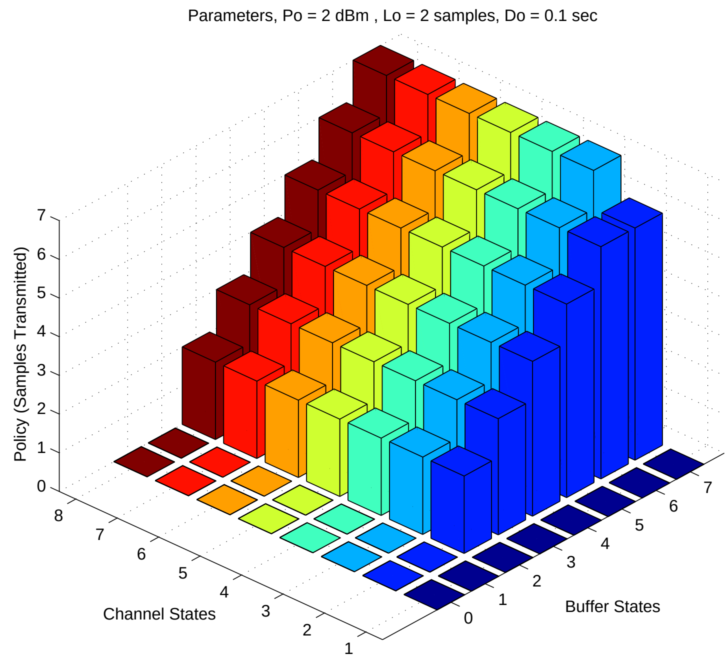

Figure 5.9: Optimal policy for average transmission rate maximization

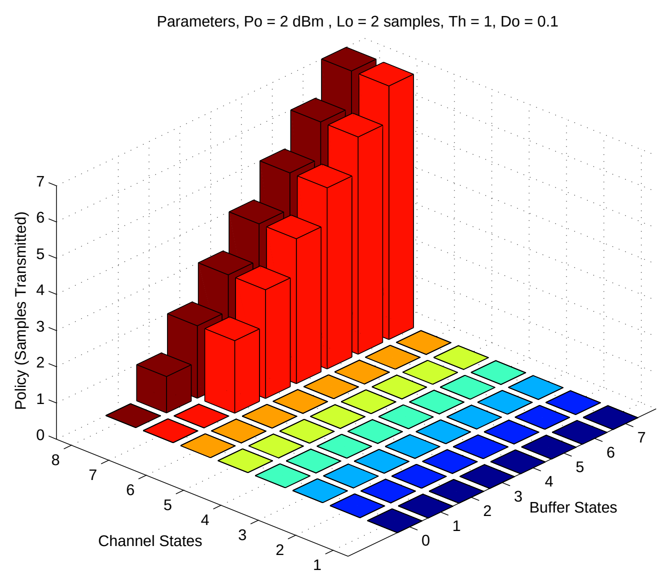

Figure 5.10: Number of sample transmissions decreases with inclusion of the average thermal increment constraint for the average transmission rate maximization

increased number of samples in the buffer also indicates that the transmitter should start sending more samples to the base station. However, in contrast with the average power minimization policy, the maximum number of samples transmitted in the best channel state with maximum number of samples in the buffer is six. This happens since we are maximizing the average transmission rate.The policy transmits as many samples as possible within the constraints. Another thing to note particularly in the policy obtained in Fig. 5.9 is that in any state of the system the number of samples transmitted is always less then or equal to the current state of the buffer. This happens because of the natural constraint applied during the simulation;i.e., number of samples transmitted should always be less then or equal to current state of the buffer.

Although, the policy plotted in Fig. 5.9 provides a better system throughput, it suffers from the fact that it can cause the thermal state of the system to increase and thus damage the subject tissues in the biosensor is implanted. In order to address this issue, the average thermal constraint given in (4.43) with the constraint parameter T_h set to 1 is included in the optimization. The optimal policy obtained is shown in Fig. 5.10. The policy indicates that when applying the thermal increment constraint, the number of samples generated in each system state is reduced. This decreases the average system throughput. The advantage however of applying this thermal constraint is that the system operates in the safe temperature zone without burning any subject tissues.

5.3.3 Monotonicity

The optimal policies obtained for the different objectives have unique behaviours. They are observed to be monotonically increasing in the channel and buffer state of the system. This means that as the channel state improves from the bad to best or the buffer state increases from empty to full, the optimal policy also increases monotonically. When embedding these policies into actual hardware, we can define the actions in terms of increasing values of channel and buffer state information. The controller can make an easy decision based on these thresholds defined by the optimal policy. This behaviour can thus help in the practical implementation of these optimal policies on biosensor hardware.

5.3.4 Comparison with the Greedy Policy

The optimal policies computed in the previous section are simulated using MATLAB and the results are compared with a greedy policy. In case of the transmission rate maximization, the greedy policy works on the principle that it always tries to transmit the maximum number samples that are allowed under the given system state without exceeding the constraints of the average loss rate, average thermal increment, average delay and average transmission power. As for the transmission power minimization, greedy policy works by transmitting the least number of samples possible without dropping below the required average transmission rate. The simulation is run five times for each number of calculation and the average results are calculated. Both policies are simulated for a different number of time

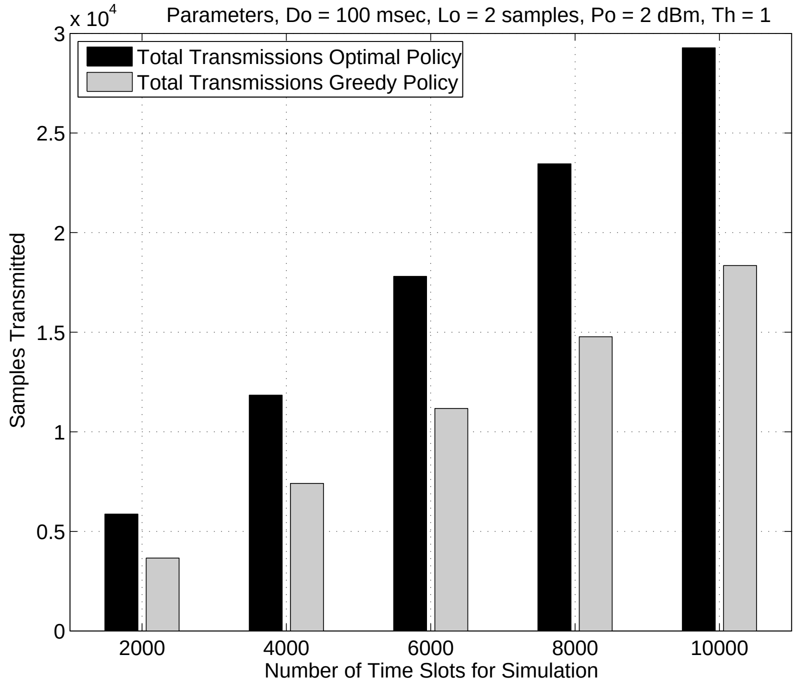

Figure 5.11: Comparison of sample transmissions for different policies with varying number of time slots

slots and their results are compared. The performance of the average transmission rate maximization policy against the greedy policy is shown in Fig. 5.11. The plot indicates that the optimal policy outperforms the greedy policy in terms of total samples transmitted. Similarly, the performance comparison of the average transmission power minimization policy is shown in Fig. 5.12. The system starts with a certain amount of initial energy and evolves based on the actions suggested by the optimal and greedy policies. The policy that makes the system run for the largest number of time slots provide a better performance. It can be observed in Fig. 5.12 that the optimal policy again outperforms the greedy policy for life time maximization and power minimization.

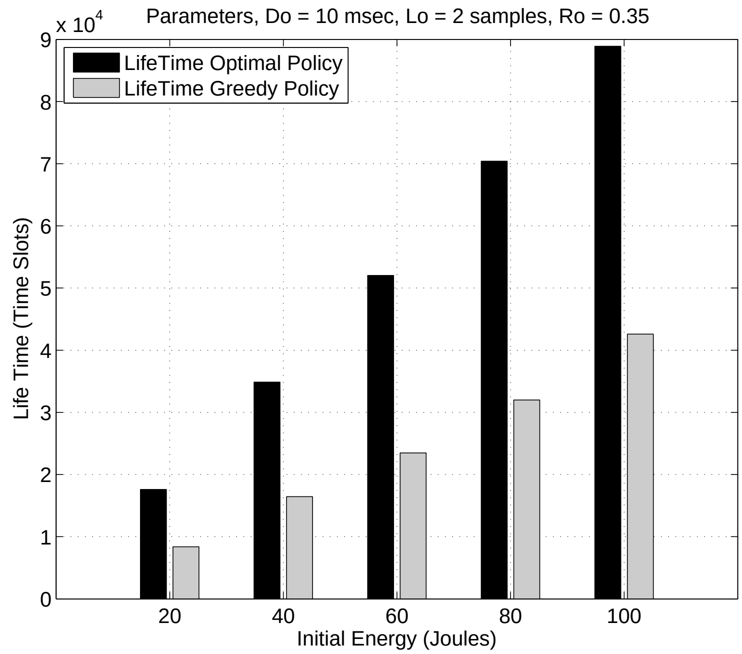

Figure 5.12: Comparison of network life time for different policies achieved by varying initial energies

5.4 Thermal Behaviour of Optimal Policies for the Thermal Increment Model

In this section we discuss the thermal behaviour of the proposed optimal policies. To simulate the thermal behaviour of the system, we start by assuming the biosensor is at normal body temperature which corresponds to zero. Each transmission increases the thermal state depending on the number of samples and the state of the wireless channel in which the transmission occurs. The step size is assumed, based upon practical observations, to be .005 degrees Celsius. A total of 600 steps causes the temperature to exceed the threshold at which the tissues start burning. Although the average transmission rate maximization policy improves the QoS by transmitting as many samples as possible, it is affected by the shear increase in

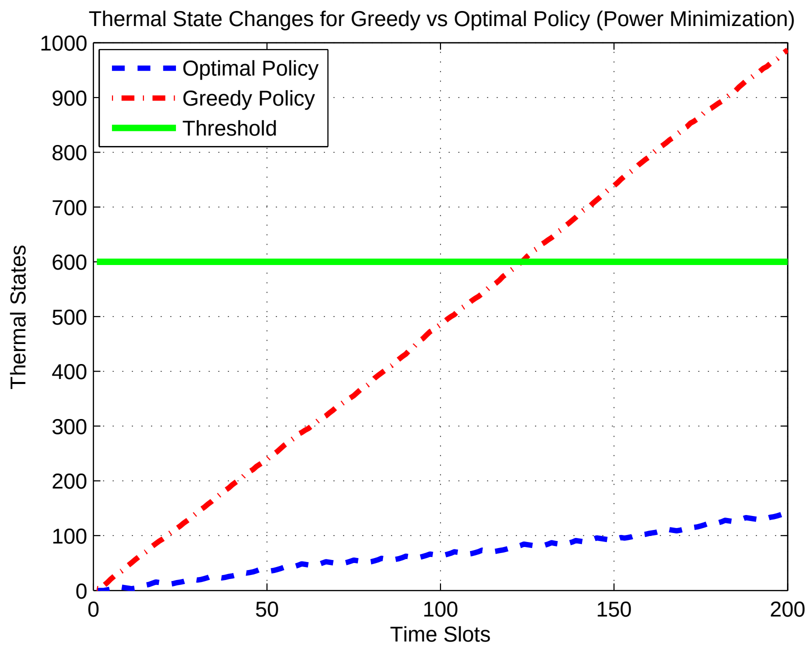

Figure 5.13: Comparison of thermal state changes for different policies

thermal state of the system.

5.4.1 Thermal Behaviour of the Average Transmission Power Minimization Policy

The thermal variation caused by the average power minimization policy are plotted against greedy policy in Fig. 5.13. The graph shows that, although, power minimization policy provides less system throughput, it can still attain better QoS by providing increased network lifetime and better thermal management. However, after certain number of time slots the system will still attain the specified threshold and the biosensor will shut down and remain in sleep mode till the temperature drops to a nominal value. This is indicated by running a long term simulation for the optimal policy in Fig. 5.14.

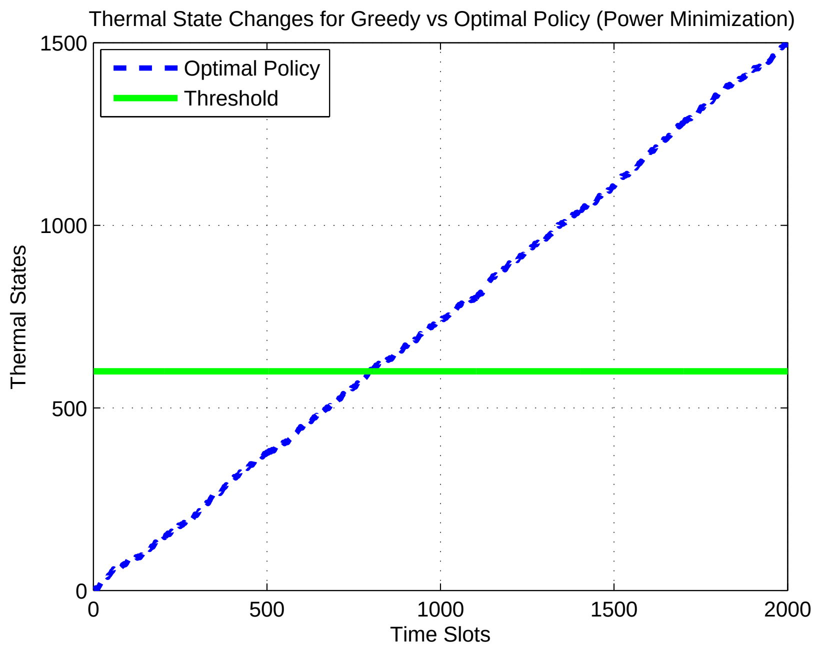

Figure 5.14: Simulated behaviour of the thermal state changes for optimal policy with the average transmission power minimization objective

5.4.2 Thermal Behaviour of Average Transmission Rate Maximization Policy

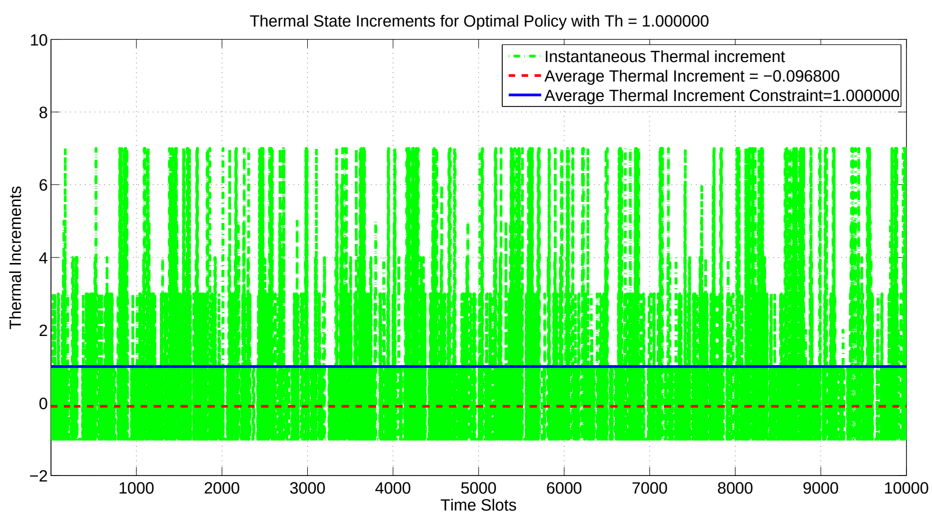

Figure 5.15: Thermal increments for optimal policy with the average transmission rate maximization

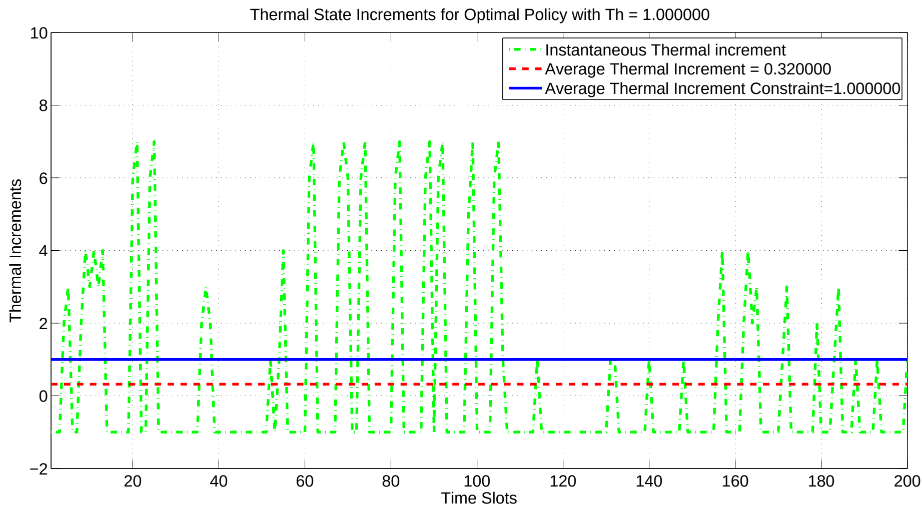

Figure 5.16: Thermal increments for optimal policy with the average transmission rate maximization, $T_h = 1$

The effect of adding the thermal increment constraint as part of the average transmission rate maximization reduces the system performance but is able to manage the temperature increase efficiently. This keeps the thermal increment constraint within bounds as shown in Fig. 5.15. The plot in Fig. 5.15 indicates that the instantaneous thermal increment oscillates around the average constraint $T_h = 1$ and the running average for thermal increment calculated from simulation is within bounds. The instantaneous variations in the thermal behaviour of the optimal policy are shown more accurately in Fig. 5.16. The plot of Fig. 5.16 is a zoomed view of the thermal behaviour for small number of time slots.

5.5 Strict Temperature Model

In this section we discuss the results obtained after implementing the strict temperature model for the average transmission rate maximization proposed in (4.49).

The results obtained are simulated and the temperature variations are observed. In the end comparison is performed with a greedy policy which indicates that the optimal policy provides better performance.

5.5.1 Average Transmission Rate Maximization

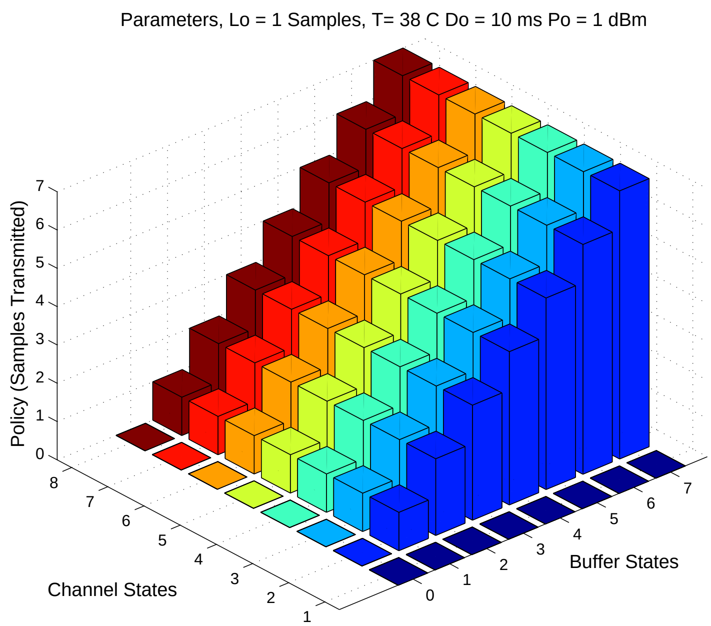

Figure 5.17: Optimal Policy for the average transmission rate maximization in the strict temperature state model,(Temperature State = 1)

We choose four temperature levels to represent temperature states in the three state model proposed for the strict temperature model. The lower and upper bounds on the temperature are set to 37^oC and 40^oC. The number of channel and buffer states are set to eight. The average arrival rate at the input of buffer is set to three. Fig. 5.17 shows the policy obtained when the objective function proposed in (4.49) is optimized subject to the constraints given in (4.50) - (4.53).

The values of the average power constraint P_O^v , temperature constraint T_h^v, delay D_O^v and loss rate L_O^v are set to $1dBm$, 38.0^oC, $10ms$ and $1Samples$ respectively. The optimal policy calculated allows transmissions only when the temperature is in state one. For higher temperature states, the policy chooses the sleep action to keep operating within the provided constraints.

5.5.2 Monotonicity

Once again the behaviour of the optimal policy obtained is observed to be monotonic in channel and buffer states. The policy ensures that more samples are transmitted as the channel and buffer state improves while keeping the average temperature and power constraints within bound. It is also observed that when the temperature is in its worst state the policy suggests to not transmit any samples in order to save the biosensor from going into threshold state. So the policy is also monotonic in terms of temperature states for the three state model.

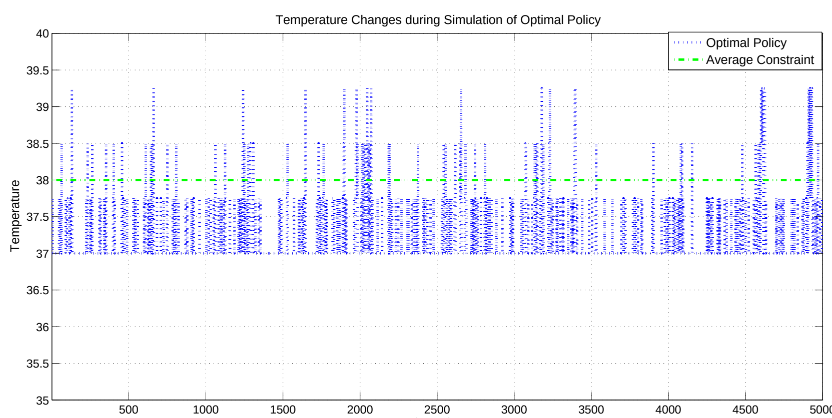

Figure 5.18: Simulated behaviour of temperature changes for optimal policy with average transmission rate maximization objective in strict temperature state model

5.5.3 Temperature Behaviour for Strict Temperature Model

Based on the parameters used in the previous section, the temperature changes of the system are simulated. Fig. 5.18 which shows that for the average transmission rate maximization the system temperature remains within bounds. Also it can be concluded that the temperature oscillates around the average temperature constraint provided in the optimization model. This model has the advantage of ensuring that the temperature never exceeds the specified bounds but it suffers from the computation point of view by requiring additional resources because of increased system states.

5.5.4 Comparison with the Greedy Policy

The optimal policy calculated for the transmission rate maximization is compared with a greedy policy that satisfies the given constraints. The greedy policy works by always trying to transmit maximum number of samples available while keeping the QoS constraints in check. A running average for all the constraints is used to make the decision in each time slot. The simulation is run five times for each number of slots and the average results are calculated. Fig. 5.19 shows the results obtained by running the simulation for up to 10000 time slots. The results indicate that the optimal policy once again outperforms the greedy policy in terms of total number of sample transmissions. However, the difference between the two is small as compared to the optimal policy for the average thermal increment model.

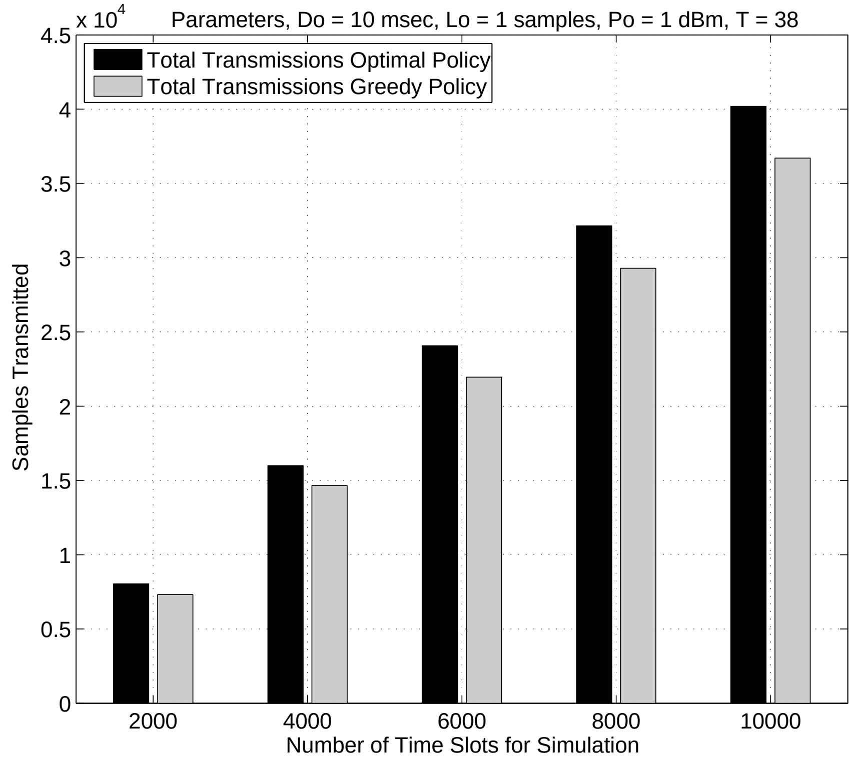

Figure 5.19: Comparison of sample transmissions for different policies achieved by the average transmission rate maximization

5.6 Summary

This chapter provides an in depth analysis of the result calculated for different operating policies for biosensor networks. The thermal increment model provides an efficient utilization of resources by having less number of system states but suffers during average transmission rate maximization. The strict temperature model, on the other hand, is able to handle the temperature changes in the biosensor node more accurately but has the disadvantage of requiring more resources as compared to the thermal increment approach.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

In this work, we have presented a new system model for biosensor networks that utilizes varying channel and buffer states information. The system is analysed using slowly varying MDP and solved with LP techniques to calculate optimal operating policies that maximize system transmission rate and lifetime under different QoS constraints. The calculated policies are then simulated and compared with greedy policy to show the viability of the proposed system.

In order to handle temperature increase in biosensor network, two approaches are proposed to solve the new system which differ in the way they handle the temperature variations of the biosensor nodes. The first, average thermal increment model, deals with the temperature increase in biosensor networks by adding a constraint on average thermal increment to the MDP model. The second, strict temperature model, introduces strict temperature variations as part of the system states during MDP formulation. The system is solved alongside temperature constraints to calculate optimal policies which outperform greedy policy for network life time and transmission rate maximization objectives. The optimal policies are also observed to be monotonic in channel and buffer states.

The simulation of the thermal behaviour of the optimal policies indicate that strict temperature model provides better control over temperature increase as compared to average thermal increment model. However, strict temperature model has the disadvantage of requiring high computation power which can be vital for battery operated biosensor nodes that have limited energy. Average thermal increment model shows promising results for average transmission power minimization since transmission power is indirectly related to thermal increase.

6.1 Future Work

The optimal policies developed provide an accurate representation of real life biosensor nodes having different QoS requirements. In the future, there is still room for improvement in the system model developed. Biosensor batter energy level is not included as part of the system state in the current model. This can be added alongside other system states to further increase the accuracy of the model. Similarly the recharge action can also be taken into consideration for biosensor networks that have wireless recharging source available. The model currently proposed is for a decentralized system in which each biosensor node have it's own system state information based on which decisions are made. The case of centralized system where a root node is responsible for gathering the state information from all the nodes and develop optimal operating policies for each node is yet to be explored.

REFERENCES

[1] M. Tubaishat and S. Madria, "Sensor networks: an overview," *Potentials, IEEE*, vol. 22, no. 2, pp. 20–23, 2003.

[2] B. Latré, B. Braem, I. Moerman, C. Blondia, and P. Demeester, "A survey on wireless body area networks," *Wirel. Netw.*, vol. 17, no. 1, pp. 1–18, Jan. 2011.

[3] A. Karmokar, D. Djonin, and V. Bhargava, "Optimal and suboptimal packet scheduling over correlated time varying flat fading channels," *Wireless Communications, IEEE Transactions on*, vol. 5, no. 2, pp. 446–456, 2006.

[4] Y. Osais, F. R. Yu, and M. St-Hilaire, "Dynamic Sensor Scheduling for Thermal Management in Biological Wireless Sensor Networks," *International Journal of Distributed Sensor Networks*, vol. 2013, pp. 1–10, 2013.

[5] Y. Osais, F. Yu, and M. St-Hilaire, "Thermal management of biosensor networks," in *Consumer Communications and Networking Conference (CCNC), 2010 7th IEEE*, 2010, pp. 1–5.

[6] F. R. Yu, Y. Osais, and M. St-Hilaire, "Optimal Management of Rechargeable Biosensors in Temperature-Sensitive Environments," *Vehicular Technology Conference Fall VTC 2010Fall 2010 IEEE 72nd*, 2010.

[7] D. Bello and G. Riano, "Linear Programming solvers for Markov Decision Processes," *2006 IEEE Systems and Information Engineering Design Symposium*, pp. 90–95, Apr. 2006.

[8] "Matlab." [Online]. Available: http://www.mathworks.com

[9] S. Xiao, A. Dhamdhere, V. Sivaraman, and A. Burdett, "Transmission power control in body area sensor networks for healthcare monitoring," *Selected Areas in Communications, IEEE Journal on*, vol. 27, no. 1, pp. 37–48, 2009.

[10] H. Wang and N. B. Mandayam, "Opportunistic file transfer over a fading channel under energy and delay constraints," *Communications, IEEE Transactions on*, vol. 53, no. 4, pp. 632–644, 2005.

[11] A. Hoang and M. Motani, "Cross-layer Adaptive Transmission: Optimal Strategies in Fading Channels," *IEEE Transactions on Communications*, vol. 56, no. 5, pp. 799–807, May 2008.

[12] E. Altman, K. Avrachenkov, I. Menache, G. Miller, B. J. Prabhu, and a. Shwartz, "Dynamic Discrete Power Control in Cellular Networks," *IEEE Transactions on Automatic Control*, vol. 54, no. 10, pp. 2328–2340, 2009.

[13] Y. Chen, Q. Zhao, V. Krishnamurthy, and D. Djonin, "Transmission scheduling for optimizing sensor network lifetime: A stochastic shortest path ap-

proach," *Signal Processing, IEEE Transactions on*, vol. 55, no. 5, pp. 2294–2309, 2007.

[14] S. Nanda, K. Balachandran, and S. Kumar, "Adaptation techniques in wireless packet data services," *Communications Magazine, IEEE*, vol. 38, no. 1, pp. 54–64, 2000.

[15] S.-L. Wu, Y.-C. Tseng, and J.-P. Sheu, "Intelligent medium access for mobile ad hoc networks with busy tones and power control," *Selected Areas in Communications, IEEE Journal on*, vol. 18, no. 9, pp. 1647–1657, 2000.

[16] E.-S. Jung and N. H. Vaidya, "A power control mac protocol for ad hoc networks," *Wirel. Netw.*, vol. 11, no. 1-2, pp. 55–66, 2005.

[17] J.-P. Ebert, B. Stremmel, E. Wiederhold, and A. Wolisz, "An energy-efficient power control approach for wlans," *Communications and Networks, Journal of*, vol. 2, no. 3, pp. 197–206, 2000.

[18] V. Krishnamurthy, "Algorithms for optimal scheduling and management of hidden markov model sensors," *Signal Processing, IEEE Transactions on*, vol. 50, no. 6, pp. 1382–1397, 2002.

[19] A. Chhetri, D. Morrell, and A. Papandreou-Suppappola, "Scheduling multiple sensors using particle filters in target tracking," in *Statistical Signal Processing, 2003 IEEE Workshop on*, 2003, pp. 549–552.

[20] R. Madan, S. Cui, S. Lall, and A. Goldsmith, "Cross-layer design for lifetime maximization in interference-limited wireless sensor networks," *Wireless Communications, IEEE Transactions on*, vol. 5, no. 11, pp. 3142–3152, 2006.

[21] J.-H. Chang and L. Tassiulas, "Maximum lifetime routing in wireless sensor networks," *Networking, IEEE/ACM Transactions on*, vol. 12, no. 4, pp. 609–619, 2004.

[22] Y. Sung, L. Tong, and H. Poor, "A large deviations approach to sensor scheduling for detection of correlated random fields," in *Acoustics, Speech, and Signal Processing, 2005. Proceedings. (ICASSP '05). IEEE International Conference on*, vol. 3, 2005, pp. 649–652.

[23] Y. Chen and Q. Zhao, "Maximizing the lifetime of sensor network using local information on channel state and residual energy," *Proceedings of the conference on information . . .*, 2005.

[24] Q. Zhao and L. Tong, "Opportunistic Carrier Sensing for Energy-Efficient," *EURASIP Journal on Wireless Communications and Networking*, vol. 2, pp. 231–241, 2005.

[25] Y. Chen and Q. Zhao, "Distributed transmission protocol for lifetime maximization in sensor networks," in *Signal Processing Advances in Wireless Communications, 2005 IEEE 6th Workshop on*, 2005, pp. 895–899.

[26] B. Latré, B. Braem, I. Moerman, C. Blondia, and P. Demeester, "A survey on wireless body area networks," *Wirel. Netw.*, vol. 17, no. 1, pp. 1–18, Jan. 2011.

[27] Crossbow-Technologies, "Mica2 and micaz motes." [Online]. Available: http://www.xbow.com

[28] V. S. et al, "Sensor networks for medical care," *Division of Engineering and Applied Science, Harvard University, Tech. Rep*, 2005.

[29] Power-Paper, "Power patch platform." [Online]. Available: http://www.powerpaper.com

[30] D. Culler, D. Estrin, and M. Srivastava, "Guest editors' introduction: Overview of sensor networks," *Computer*, vol. 37, no. 8, pp. 41–49, 2004.

[31] L. Schwiebert, S. K. Gupta, and J. Weinmann, "Research challenges in wireless networks of biomedical sensors," in *Proceedings of the 7th annual international conference on Mobile computing and networking*, ser. MobiCom '01. ACM, 2001, pp. 151–165.

[32] E. Corporation, "Geodesic sensor networks." [Online]. Available: http://www.egi.com

[33] International Electrotechnical Commission and International Electrotechnical Commission. Technical Committee 62, *Medical electrical equipment. Part 2-33, Particular requirements for the basic safety and essential performance*

of magnetic resonance equipment for medical diagnosis. International Electrotechnical Commission.

[34] A. Hirata, G. USHIO, and T. Shiozawa, "Calculation of temperature rises in the human eye exposed to EM waves in the ISM frequency bands," *IEICE Transactions on . . .*, vol. E83-B, 2000.

[35] Q. Tang, N. Tummala, S. K. S. Gupta, and L. Schwiebert, "Communication scheduling to minimize thermal effects of implanted biosensor networks in homogeneous tissue," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 7, pp. 1285–1294, 2005.

[36] H. H. Pennes, "Applied physiology," *Journal of Applied Physiology*, vol. 1, no. 1, pp. 93–122, 1948.

[37] D. M. Sullivan, *Electromagnetic simulation using the FDTD method.* IEEE Press, 2000.

[38] C. Tan and N. Beaulieu, "On first-order markov modeling for the rayleigh fading channel," *Communications, IEEE Transactions on*, vol. 48, no. 12, pp. 2032–2040, 2000.

[39] H. S. Wang and N. Moayeri, "Finite-state Markov channel- a useful model for radio communication channels," *IEEE Transactions on Vehicular Technologies*, vol. 44, no. 1, pp. 163–171, 1995.

[40] D. Zhang, "Analysis on Markov modeling of cellular packet transmission," 2002, pp. 876–880.

[41] R. Berry and R. Gallager, "Communication over fading channels with delay constraints," *Information Theory, IEEE Transactions on*, vol. 48, no. 5, pp. 1135–1149, 2002.

[42] R. A. Berry and R. G. Gallager, "Communication over fading channels with delay constraints," *IEEE Transactions on Information Theory*, vol. 48, pp. 1135–1149, 2002.

[43] M. L. Puterman, *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. John Wiley and Sons, 1994.

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