

Thermal Management of Biosensor Networks

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Abstract—Biosensors are a very promising technology that will take healthcare to the next level. However, there are obstacles that must be overcome before the full potential of this technology can be realized. One such obstacle is that the heat generated by implanted biosensors may damage the tissues around them. Dynamic sensor scheduling is one way to manage the heat generated by implanted biosensors. In this paper, the dynamic sensor scheduling problem is formulated as a Markov decision process. Not like previous works, the temperature increase in the tissues caused by heat is incorporated into the model. The solution of the model gives an optimal policy that when executed, it will result in the maximum possible network lifetime under a constraint on the maximum temperature tolerable by the patient's body. The optimal policy is compared with two policies one of which is specifically designed for biosensor networks. Numerical and simulation results show the validity of the model and superiority of the optimal policy produced by the model in terms of both network lifetime and temperature increase.

Keywords—Biosensor networks, body networks, implanted biosensors, thermal effects, bioheating, temperature increase, dynamic sensor scheduling, Markov decision process.

I. INTRODUCTION

Investigating the potential of Wireless Sensor Networks (WSNs) in healthcare is inevitable. This is due in part to the needs of the healthcare sector and in part to the technological push. For example, WSNs are believed to enable the paradigm of pervasive healthcare. That is, healthcare that is available to anyone, anytime and anywhere with the potential to successfully enhance quality of life while reducing healthcare cost.

Biosensors are a key player in facilitating pervasive healthcare. They are tiny wireless devices implanted into the body of a patient or worn around a part of his body to monitor and detect abnormalities and then relay data to the physician or provide therapy on the spot. Consider, for instance, a glucose biosensor which monitors the blood glucose level in a diabetic patient. This sensor can be used to optimally control the infusion of insulin into the patient or to initiate a prompt medical intervention.

Implanted biosensors may have a thermal impact on the tissues surrounding them. They generate heat which cannot be dissipated easily. Power dissipation and radiation due to wireless communication and recharging are the major sources of heat. The generated heat manifests itself as a temperature increase inside the tissues. Thus, if the blood flow is less than optimal, the affected tissues might be damaged.

Prior works have suggested the use of sensor scheduling to achieve goals such as minimizing the thermal effects of biosensors [1] and maximizing the lifetime of WSNs [2]. However, the use of dynamic sensor scheduling to thermally manage biosensor networks has not been addressed before in the literature. As a first step in this direction, in this paper, we model the thermal management problem in biosensor networks as a Markov Decision Process (MDP) whose state includes the temperature, remaining energy and state of the wireless channel at each biosensor. The model is solved to find the optimal policy which dictates how the biosensor network should be operated in order to avoid a hazardous temperature increase. The optimal policy is compared with two recently published heuristic policies.

The remainder of the paper is organized as follows. First, an overview of related works is given. Second, the system model is described. After that, the MDP formulation of the system model is presented. An example is provided in section V to illustrate an application of the model. Then, in section VI, the optimal policy produced by the proposed MDP model is compared with two heuristic policies using simulation. Also, a discussion and insights drawn from our experience are given. Finally, some conclusions are offered.

II. RELATED WORK

There is a growing interest in biosensor networks. In particular, the analysis and design of efficient sensor scheduling policies is attracting the most attention. For example, in [1], the effect of leadership rotation in a cluster-based biosensor network is studied. It was observed that rotating the role of which node collects measurements from other sensors and deliver them to the base station can significantly reduce the temperature increase in tissues due to wireless communication. The computation of an optimal rotation sequence involves using the Pennes's bioheat equation [3] and the Finite-Difference Time-Domain (FDTD) method [4] to calculate the temperature increase due to a sequence. Because of its time requirement, the authors proposed another scheme to calculate the temperature increase. It is referred to as the Temperature Increase Potential (TIP). It efficiently estimates the temperature increase of a sequence. Using this scheme and a genetic algorithm, they were able to find the minimum temperature increase rotation sequence. They, however, did not consider the effect of the wireless channel and limited energy.

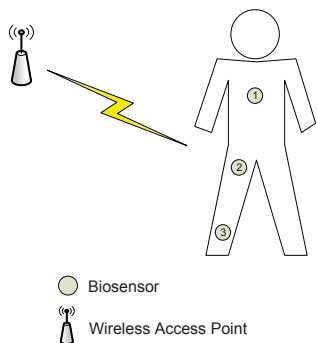


Fig. 1. A patient with three biosensors implanted into his body.

On the other hand, in [2], transmission scheduling for maximizing network lifetime when the wireless access point has the information of all sensors' instantaneous channel realizations is considered. The problem is formulated as an MDP which incorporates the effect the wireless channel and remaining energy at each sensor. The MDP formulation contains an inevitable terminating state which makes the sensor scheduling problem an instance of the stochastic shortest path problem. The MDP model is also extended to incorporate Markovian fading channels. Two heuristic policies are analyzed. They are the opportunistic and conservative scheduling policies. In the former, the sensor with the best channel is always selected. In the latter, however, the sensor with the most residual energy is always selected. It was concluded that network lifetime maximization requires an optimal tradeoff between channel state information and remaining energy at each sensor.

Another interesting line of research deals with biosensor networks with energy harvesting capabilities [5]. In this type of WSNs, each sensor has an energy harvesting device that collects energy from ambient sources such as vibration, light and heat. In this way, the more costly recharging method which uses radiation is avoided. The interaction between the battery recharge process and transmission with different energy levels was studied in [6]. The proposed policies utilize the sensor's knowledge of its current energy level and the state of the processes governing the generation of data and battery recharge to select the appropriate transmission mode for a given state of the network.

Clearly, from the above discussion, there is a gap in our current knowledge about biosensor networks. The interplay between the initial energy a biosensor has, its temperature and the state of the wireless channel has not been studied and thus the optimal operating policy is unknown. This is where our work differs from the above.

III. SYSTEM MODEL

A biosensor network is a system composed of tiny wireless devices implanted into the body of a human being or animal and a wireless access point. Figure 1 shows a biosensor network consisting of three biosensors implanted into the body of a patient and one wireless access point. The wireless access point initiates the data collection process by determining which

biosensor should transmit its measurement. A biosensor is selected for transmission based on the current network state and some policy. The wireless access point is assumed to know the channel realization and state of each biosensor at each point in time.

A biosensor network can mathematically be modeled as a discrete system which evolves in discrete time. Thus, the time axis is divided into slots of equal duration ΔT and time $t \in \mathbb{Z}^+$ is the time interval $[t\Delta T, (t+1)\Delta T)$. Control can only be exercised at the beginning of a time slot and not at any other time during the slot. A state represents the condition of the system at the beginning of a slot. The goal is to find a policy which specifies which control action to take in each state. A policy is said to be stationary if the action it chooses at time t depends only on the state of the system at time t .

Let Π be the set of biosensors that have been surgically implanted in the body of a patient and at known locations. Also, let Ω_i be the set of biosensors which are neighbors to biosensor i . Different criteria can be used to compute this set. In this work, the Euclidean distance between biosensors is used.

The location of a biosensor represents a critical point since it experiences the maximum temperature increase. This is because the tissues surrounding a biosensor might be heated continuously due to the local radiation generated by the biosensor itself and the radiation generated by its neighbors. Therefore, in each time slot t , the state of a biosensor i is characterized by two variables which are the current temperature $T_t(i)$ and remaining energy $E_t(i)$.

Each biosensor i has a battery with an initial energy of \mathcal{E}_0 . The energy required for a biosensor i to successfully transmit its measurement to the base station is determined by the state of the wireless channel in time slot t in which it is scheduled. This transmission energy is a random variable that is denoted by $W_t(i)$ and is IID over all sensors and time slots. Due to hardware and power limitations, $W_t(i)$ is discretely distributed over a finite set $\{\epsilon_1, \epsilon_2, \dots, \epsilon_L\}$, where $0 < \epsilon_1 < \epsilon_2 < \dots < \epsilon_L < \infty$ and ϵ_j is the energy consumed by a sensor in transmitting its measurement at the j^{th} power level.

In each time slot, the energy and temperature of the scheduled sensor change according to its transmission energy requirement. Also, the temperatures of its neighbors change accordingly. On the other hand, the energies of non-neighboring sensors remain the same and their temperatures decrease. In order to compute the exact value of the temperature at any location and time, the Pennes's bioheat equation and the FDTD method must be used. The FDTD method is a technique that transforms the bioheat equation to a discrete form with discrete time and space steps. However, due to the large simulation time required before the temperature increase or decrease reaches a steady state, this approach is not followed here. Instead, the temperature decrease is assumed to be a constant reduction which occurs whenever the sensor is not transmitting and not a neighbor of a transmitting sensor. Also, the temperature increase is assumed to be directly proportional

to the energy consumed by the transmitting sensor.

Therefore, at the end of each time slot, the energy level at each sensor i is given by the following equation:

$$E_{t+1}(i) = \begin{cases} E_t(i) & \text{if } i \neq a \\ E_t(i) - W_t(a) & \text{if } i = a \end{cases} \quad (1)$$

where a is the index of the sensor chosen for transmission. Similarly, the temperature of each sensor i is given by the following equation:

$$T_{t+1}(i) = \begin{cases} \mathcal{F}(T_t(i), W_t(a)) & \text{if } i = a \mid i \in \Omega_a \\ T_t(i) - \tau & \text{if } i \neq a \ \& \ i \notin \Omega_a \end{cases} \quad (2)$$

where \mathcal{F} is a function of the transmission power and current temperature of the sensor scheduled for transmission and τ is the amount by which the temperature of a non-neighboring sensor decreases. The symbol \mid denotes the logical OR operator.

Finally, the wireless channel between the biosensors and wireless access point is a Markovian fading channel. Hence, the transmission energy requirement for a biosensor i follows a Markov chain with L states and transition probabilities $P[W_{t+1}(i) = w' \mid W_t(i) = w]$, where $w, w' \in \{\epsilon_j\}_{j=1}^L$.

IV. MDP FORMULATION

The purpose of the MDP formulation of the system described in the previous section is to find a policy π that prescribes the best action to take in each state of the system so as to maximize the long-term expected lifetime of the system. The policy π is a stationary policy which means that it is independent of time and depends only on the state of the system. Next, we give the details of the MDP model.

A. State Set

The state of the system with $|\Pi|$ biosensors at time t is described by a $(3 \times |\Pi|)$ -dimensional vector. That is,

$$s_t = \{(T_t(1), E_t(1), W_t(1)), (T_t(2), E_t(2), W_t(2)), \dots, (T_t(|\Pi|), E_t(|\Pi|), W_t(|\Pi|))\} \quad (3)$$

Let S be the set of possible system states. Then, the number of possible system states is $|S| = |T|^{|\Pi|} \times |E|^{|\Pi|} \times |W|^{|\Pi|}$, where $|T|$, $|E|$ and $|W|$ are the numbers of possible temperatures, residual energies and transmission energy levels, respectively.

The system enters a terminating state when any one of the following two conditions is true:

- 1) Temperature of any biosensor is harmful (i.e., $T_t(i) > T_{max}$, where T_{max} is a maximum threshold on the allowed temperature increase), and
- 2) A biosensor cannot transmit its measurement due to lack of enough energy (i.e., $E_t(i) < W_t(i)$).

Once the system is in a terminating state, the system must be halted to protect the patient. The system can then be restored to an initial state by recharging the biosensors and letting them cool down.

B. Action Set

In each time slot, based on the current state of the system, the base station chooses an action (i.e., a biosensor to transmit its measurement). The set of possible actions consists of the indexes of all biosensors. In other words, the set of actions available in each state $s \in S$ is $A(s) = \{1, 2, \dots, |\Pi|\}$.

C. Reward Function

Let $R(s, a)$ be the instantaneous reward earned by the network due to action $a \in A(s)$ when the system is in state $s \in S$. Since the goal is to maximize the expected network lifetime, the reward function can be defined as

$$R(s, a) = 1$$

which assigns a unit reward to each time slot as long as the network is in a non-terminating state. Therefore, the expected sum of rewards obtained before the network reaches a terminating state represents the network lifetime. It should be pointed out that the expectation is taken over all possible state sequences generated by a given policy.

D. Transition Probability Function

The behavior of the system is described by $|A| \times |S| \times |S|$ transition probability matrices. Each matrix is denoted by $\mathbb{P}_{s_t, s_{t+1}}(a)$ which is the probability that choosing an action a when in state s_t will lead to state s_{t+1} . More formally, $\mathbb{P}_{s_t, s_{t+1}}(a)$ can be rewritten as the following:

$$\mathbb{P}[s_{t+1} | s_t, a = k] = \prod_{i \in \Pi} \left\{ P[T_{t+1}(i) | T_t(i), W_t(i), a = k] \times P[E_{t+1}(i) | E_t(i), W_t(i), a = k] \times P[W_{t+1}(i) | W_t(i)] \right\} \quad (4)$$

E. Value Function

The thermal management problem is formulated as an infinite-horizon MDP using the average reward criterion [7]. So, let $V_\pi(s_0)$ be the expected network lifetime given that the policy π is used with an initial state s_0 . Then, the maximum expected network lifetime $V^*(s_0)$ starting from state s_0 is given by

$$V^*(s_0) = \max_{\pi} V_\pi(s_0) \quad (5)$$

The optimal policy π^* is the one that achieves the maximum expected network lifetime at all non-terminating states. Hence, it gives the optimal sensor transmission schedule.

The Relative Value Iteration (RVI) algorithm [8] is used to numerically solve the following recursive equation for $n > 0$

$$V_n(s) = \max_{a \in A(s)} \left[R(s, a) + \sum_{s_{t+1} \in S} \mathbb{P}(s_t, s_{t+1}, a) V_{n-1}(s_{t+1}) \right] \quad (6)$$

In (6), the subscript n denotes the iteration index. As $n \rightarrow \infty$, $V_n \rightarrow V^*$.

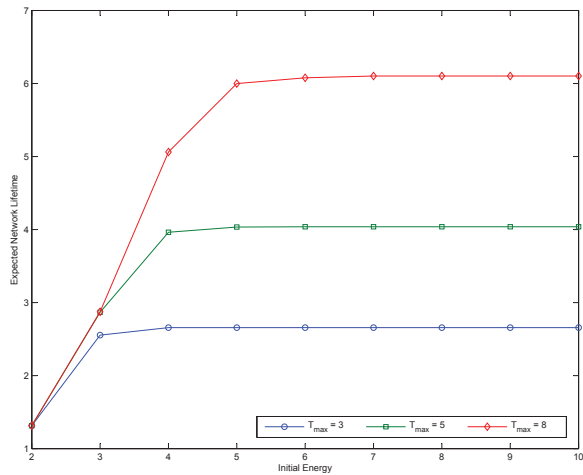


Fig. 2. Expected network lifetime vs. initial energy for different values of T_{max} .

V. EXAMPLE

In this section, we use the MDP formulation presented earlier to model the biosensor network shown in Figure 1. The biosensors are indexed from one to three. The neighbors of each biosensor are as follows:

- $\Omega_1 = \{2\}$
- $\Omega_2 = \{1, 3\}$
- $\Omega_3 = \{2\}$

Also, the \mathcal{F} function in (2) is defined for each biosensor i as

$$\mathcal{F}(T_t(i), W_t(a)) = T_t(i) + W_t(a).$$

The channel for each biosensor is modeled as a two-state Markov chain with the following transition probability matrix

$$\begin{bmatrix} 0.3 & 0.7 \\ 0.2 & 0.8 \end{bmatrix}.$$

A biosensor requires k units of energy to successfully transmit its measurement when its channel is in state $k \in \{1, 2\}$.

The MDP model of the above system is solved using the RVI algorithm. The initial state of the network is assumed to be $\{(0, \mathcal{E}_0, 1), (0, \mathcal{E}_0, 1), (0, \mathcal{E}_0, 1)\}$. The expected network lifetime is the value calculated by the RVI algorithm for the initial state.

Figure 2 shows the expected network lifetime for different levels of initial energy (\mathcal{E}_0) and maximum allowed temperature increase (T_{max}). For example, for $T_{max} = 3$ (i.e., a maximum temperature of three units is allowed), the maximum expected network lifetime is 2.875. This can be achieved with an initial energy of 4 units. As the curve for $T_{max} = 3$ shows, increasing the initial energy will not increase the expected lifetime due to the limit on the maximum allowed temperature increase.

The initial energy of a biosensor might also become a limiting factor. For example, for $T_{max} = 8$, \mathcal{E}_0 limits the maximum expected lifetime over the range of initial energies from 2 to 6. After that, T_{max} becomes the limiting factor. In this example, the maximum expected network lifetime which

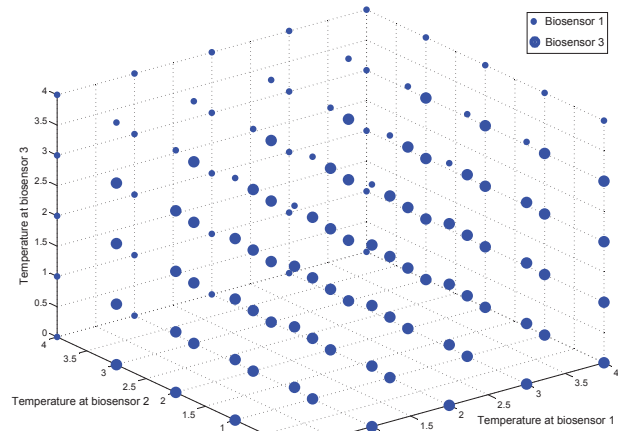


Fig. 3. Optimal actions when $E(1) = E(2) = E(3) = 3$, $W(1) = W(2) = 2$ and $W(3) = 1$, $T = 5$ and $\mathcal{E}_0 = 5$.

can be achieved with $T_{max} = 8$ is 7.265 with an initial energy of 7 units.

Another interesting issue is the amount of energy which remains in biosensors after the system is halted due to a high temperature increase. For example, from Figure 2, it can be seen that for $\mathcal{E}_0 = 4$, increasing T_{max} leads to a noticeable increase in the expected lifetime of the network. This indicates that the amount of initial energy must be determined carefully. This is because an excessive amount of remaining energy means that the patient has been exposed to an unnecessary temperature increase when the biosensors implanted in his body were charged. Thus, the measurement process has been started on already heated organs.

Figure 3 shows the actions the optimal policy makes when the remaining energy at each biosensor is fixed at three and the transmission energies of biosensors 1 and 2 are both two and that of biosensor 3 is one. \mathcal{E}_0 and T_{max} are both 5. After analyzing the data, it is found that biosensor 3 is selected for transmission in 64% of the system states since it results in the minimum temperature increase. This is obvious since only one unit of energy is required for a successful transmission and the size of its neighborhood is one. Biosensor 2 is never selected. Biosensor 1, however, is selected when the temperature at biosensor 3 or its neighbor (biosensor 2) is 4. This is because if any one of them is selected, the system will enter a terminating state. So, biosensor 1 is selected to let biosensor 3 cool down and thus lengthen the network lifetime or to distribute heat evenly if the network is going to enter a terminating state.

VI. SIMULATION RESULTS AND DISCUSSION

In this section, we compare the performance of the optimal policy produced by the proposed MDP model with that of the TIP-based and most residual energy policies. The biosensor network in Figure 1 is simulated with $T_{max} = 7$. Each data point is the result of 1000 simulation runs. The simulator is written in Matlab [9].

The TIP-based policy (or the optimal rotation sequence) is computed as described in [1]. The optimal sequence is (3,1,2).

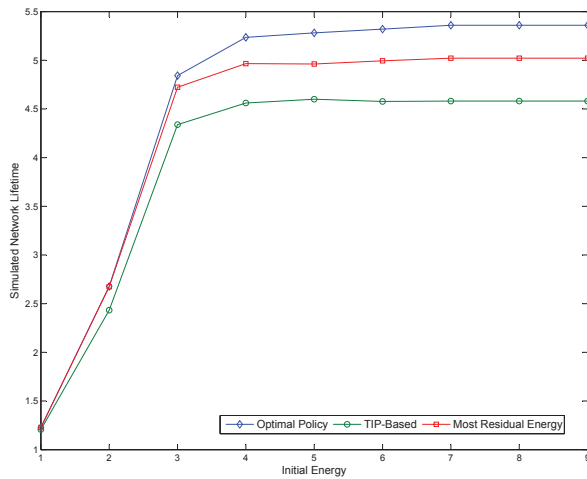


Fig. 4. Simulated network lifetime vs. initial energy for different policies.

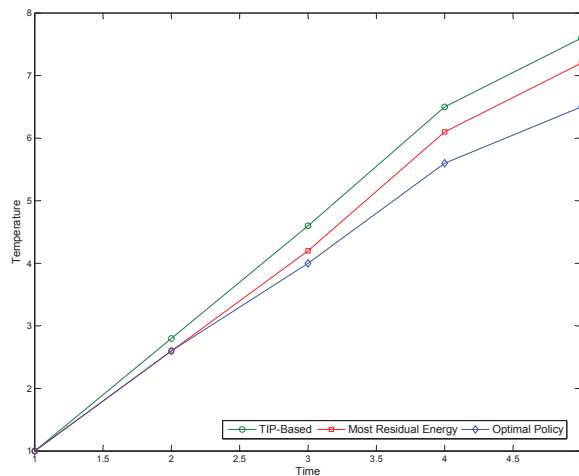


Fig. 5. Temperature at biosensor 2 for different policies.

The peak potential is 0.148 and is experienced by biosensor 2.

Figure 4 shows the simulated lifetime of the biosensor network when the initial energy is varied from 2 to 10. Essentially, the network lifetime increases as the initial energy increases. However, after a threshold (around 4), the lifetime curve starts to level off for all policies. Again, this is because the limit on the maximum allowed temperature increase is reached.

Clearly, the optimal policy outperforms the other two policies. The TIP-based policy performs the worst. The main reason for its poor performance is that the TIP-based policy does not account for the effects of the wireless channel. On the other hand, the policy based on the most residual energy performs better than the TIP-based policy. This is because it always chooses the sensor which consumes the least amount of energy for transmission. Hence, the gap between its curve and that of the optimal policy is smaller. Nevertheless, its performance cannot reach the performance of the optimal policy since temperature is not considered explicitly.

Next, the performance of the three policies in terms of temperature increase is compared. The initial energy is fixed at $\mathcal{E}_0 = 7$. The temperature at biosensor 2 is chosen as a metric. This is because biosensor 2 belongs to the neighborhoods of both biosensors 1 and 2. Thus, it might be heated continuously.

Figure 5 shows the temperature at biosensor 2 over four time slots. As expected, the TIP-based policy gives the maximum temperature increase. A closer examination of the simulation data reveals that biosensor 2 has indeed been continuously heated. This in turns leads to a larger temperature increase and thus shorter lifetime since the maximum allowed temperature is approached very fast.

Both the most residual energy and optimal policies give a significant improvement over the TIP-based policy. The performance of the two policies is slightly the same over the first two time slots. Then, the optimal policy shows a lower temperature increase over the remaining time slots.

The above observation is very interesting since the goal of the TIP-based policy is to give a minimal temperature increase rotation sequence. However, since the the wireless channel and its dynamics are not taken into account, the precomputed rotation sequence will most probably lead to a larger temperature increase when implemented in practice.

VII. CONCLUSIONS

The future of biosensor networks is bright. However, much remains to be done to define the full potential of this technology. In this paper, we have taken one step further in understanding the thermal management problem in biosensor networks. The problem is modeled as a Markov decision process to obtain an optimal policy for the operation of the biosensor network. The optimal policy outperforms the policies based on the most residual energy and temperature increase potential. This is because the optimal policy gives the best balance between transmission energy consumption and the resulting temperature increase.

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