Energy Efficient Joint Scheduling and Power Control for Wireless Sensor Networks

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***Abstract*— We investigate the problem of energy efficiency in TDMA link scheduling with transmission power control using a realistic SINR-based interference model, given packets of a set of links to be transmitted within a latency bound. First we formulate a fundamental optimization problem (TJSPC) that provides tunable tradeoffs between energy, throughput and latency through a single parameter β. We present both exponential and polynomial complexity solutions to this problem and evaluate their performance. Our results show that for moderate traffic loads, with appropriate tuning of parameters, major energy savings can be obtained without significantly sacrificing throughput. We then investigate the scheduling and power control problem with the objective of minimizing the total transmission energy cost under the constraint that all transmission requests are satisfied (JSPC-TR). We present an iterative approach to solve JSPC-TR that leverages the heuristics for TJSPC and converges rapidly to the setting of β which achieves energy efficiency while guaranteeing data delivery.**

I. Introduction

TDMA scheduled medium access is generally more energy efficient than random access, and is particularly suitable for implementation with low overhead when traffic is predictable or slowly changing. Several studies have investigated TDMA scheduling techniques for ad hoc and sensor networks [1], [2], [3], [6], [4], [5], [7]. In these studies, typically a simple model for interference is used where a receiving node sees interference from another transmitter if and only if it is within some nominal range R_I. This model, while useful in providing a simple graph-coloring approach to TDMA scheduling, can be quite misleading in practice. In reality, simultaneous wireless transmissions within the nominal range do not necessarily collide if the signal to interference plus noise ratios (SINR) at the corresponding receivers are sufficiently high; and, at the other extreme, aggregate interference from multiple transmitters that are well beyond the nominal range can be high enough to cause collisions.

Another concern with many studies of TDMA in wireless ad hoc and sensor networks is that they ignore the possibility of variable transmission power. In practical systems this can be an important tunable parameter for reliable and energy-efficient communication, because higher transmit powers can increase the SINR at the receiver to enable successful reception on a link, and lower transmission power can mitigate interference to other simultaneously utilized links.

We treat in this work TDMA link scheduling using a realistic SINR-based interference model, explicitly taking transmission power control into account. This approach to joint scheduling and power control was first taken by ElBatt and Ephremides [9], [10], followed by others including [11], [12], [13], [14], [18]. Given a set of one-hop links and number of packets that need to be transmitted within a certain number of slots, the *scheduling problem* is to decide in each time slot which source-destination pairs communicate while *power control problem* is to decide the transmission power of source nodes in a given slot.

In these prior works, the primary objective of the link scheduling algorithm is to maximize the number of simultaneous transmissions which maximize the throughput. While the power control phase minimizes transmission powers on the scheduled links, link scheduling can not guarantee power efficiency, because maximizing the concurrent transmissions increases inter-sender interference and hence the total required transmission power. Potentially significant energy savings are possible through alternate link schedules. Even further energy savings may be achievable by trading off throughput and latency.

In this paper, we study the energy efficient joint scheduling and power control problem. Our contributions in this work are four-fold. First, we formulate joint scheduling and power control as a novel optimization problem that provides tunable tradeoffs between throughput, energy and latency. We show that the prior formulations in [9], [11] can in fact be treated as special cases of our formulation. Second, while the optimization problem that we formulate is NP-hard, we present both exponential and polynomial complexity greedy based heuristic algorithms. Third, we show the performance of these algorithms through simulation results and demonstrate the energy-latency-throughput tradeoffs that can be achieved with joint link scheduling and power control. Interestingly, we find that, at least for moderate loads, major energy savings can be obtained without significantly sacrificing throughput. Finally, we study the the energy efficient joint scheduling and power control problem with the objective of minimizing minimize the total energy cost subject to all packets of the links are transmitted within a latency bound.

The rest of the paper is organized as follows. In section II, we define the energy efficient joint scheduling and power control problem. We study the tunable joint link scheduling and power control problem in section III. In section IV, we investigate the problem of joint scheduling and power control with transmission request constraint. We evaluate the performance by simulations in section V. We then discussed the related works in section VI and conclude our work in section VII..

II. Energy, Latency and Throughput Tradeoffs in Joint Scheduling and Power Control

A. Application Scenario

We first describe the basic application scenario and assumptions.

1) Consider a static wireless sensor network, all nodes are equipped with same radio with omni-directional antennas and share the same channel. The transmission power of the radio can be adjusted continuously [1], with constraints on the minimum and maximum transmission power levels. The radio data rate is fixed.
2) Consider a general application in wireless sensor network, each sensor node samples the environment periodically. A node either reports to sink or communicate with neighbors when an interesting event is detected. Sensing data need to be processed or reported before a latency deadline, such as in fire detection or real time target tracking applications.
3) The deadline can be per-hop deadline or end-to-end deadline. In case of end-to-end deadline, we divide the end-to-end deadline by the number of hops so we have a per-hop deadline for each link on the path. This is reasonable since end-to-end deadline should be proportional to the number of hops on the path.
4) Time is divided into equal sized slots that are long enough for one packet transmission and grouped into frames. Some works on TDMA focus on minimizing the length of the frame subject to the constraint that every node or link is assigned at least one slot. In this work, however, the frame length is chosen according on the per-hop latency deadline.
5) Each node generates random number of packets of fixed length which need to be transmitted in one TDMA frame. This is called a transmission request. Packets not transmitted within current time frame are dropped.

B. Interference Model

The interference model that we consider is a SINR-based TDMA system. Let $G = (V, E)$ be the wireless sensor network, with V representing the set of nodes in the network and E, the set of communication links. Given a link $(i, j) \in E$, i is the sending node and j is the receiving node. A link is called active in a slot if node i transmits data packet to node j in that slot. We refer all active links in a single time slot as a *transmission scenario*, or *transmission set*. The signal to interference and noise ratio ($SINR$) for link (i, j) is defined as:

$$SINR_{ij} = \frac{\alpha_{ij} P_i}{N_j + \sum_{k \neq i} \alpha_{kj} P_k} \tag{1}$$

[1]In practice, there may only be several discrete transmission power levels. This assumption, however can simplify the analysis and does not affect the correctness of the algorithm.

where α_{ij} is the propagation attenuation of the signal from node i to node j, which is proportional to $\frac{1}{d_{ij}^n}$, where n is the path loss factor. We assume α_{ij}s changes slowly so that we can regard α_{ij} as constant for the duration of a time frame in the following discussion. We present an iterative approach to solve JSPC-TR that leverages the heuristics for TJSPC and converges rapidly to the setting of β which achieves energy efficiency while guaranteeing data delivery. . N_j is the environment noise power at receiver j. P_i and P_k are the transmission powers of sending node i and k separately.

A data transmission on a link (i, j) can be successfully received at the receiver only if the corresponding $SINR$ on that link is equal or greater than a given threshold γ:

$$SINR_{ij} \geq \gamma \tag{2}$$

C. Power Control

If there is only one active link (i, j), node i only needs to transmit at a power level just high enough to satisfy $SINR_{ij} \geq \gamma$. However, if there are multiple active links in the same time slot, because of the interfere among each other each node has to transmit at higher power in order to meet the $SINR \geq \gamma$ requirements, which increases the interference in return. The power control problem is to compute a set of transmission power for all links in a transmission scenario by solving the following optimization problem:

$$\begin{array}{ll} \text{minimize} & \sum_{ij} P_{ij} \\ \text{subject to} & SINR_{ij} \geq \gamma \\ & P_{min} \leq P_{ij} \leq P_{max},\ \forall ij \text{ links} \end{array} \tag{3}$$

Some distributed power control algorithms have been proposed for cellular network [8] and wireless ad hoc networks [9], which we will use directly in this paper.

We call a transmission scenario/set *feasible* if a set of transmission powers are available such that the $SINR$ requirements of all receivers in the transmission scenario are satisfied. A set is called a *maximal transmission set* if adding any additional active link will result in an infeasible transmission set. All subsets of a *maximal transmission set* are also *feasible transmission sets*. We refer the sum of the transmission power of all active links in a transmission scenario as its energy cost.

We make two important observations about the total transmission power of a feasible transmission scenario.

1) Two feasible transmission scenarios with same number of concurrent transmissions could have significantly different costs because of the different interference among the the links, depending on the location and wireless channel of the links.
2) A feasible set's cost is always larger or equal to sum of the costs of its subsets.

$$\begin{array}{ll} \text{If} & S_j = \bigcup_k S_{jk} \\ \text{then} & C_j \geq \sum_k C_{jk} \end{array} \tag{4}$$

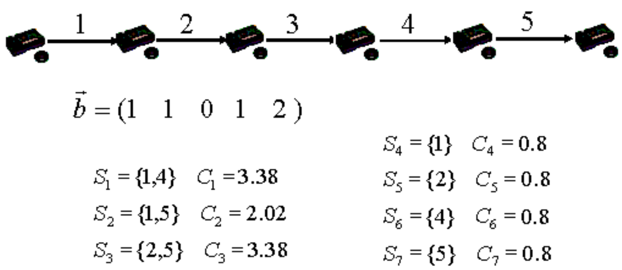


Fig. 1. Illustration of energy efficient scheduling. $\vec{b}$ is the number packets need to be transmitted for each link. S are all possible feasible transmission scenarios. C are the total transmission power of the transmission scenarios.

TABLE I
SUMMARY OF THE NOTATIONS

$e = (i, j)$	A link with i the sender and j the receiver
T	Number of slots in a TDMA frame
$\vec{b}$	Transmission request: Number of packets need to be sent for each link
S	The collection of all feasible transmission set, S_k being one of the set
$S_k(e)$	1 if link e is active in transmission set S_k
M	$\|S\|$, number of feasible transmission set
C_k	Energy cost of transmission set S_k
$\vec{x}$	The scheduling solution: x_k is the number of times S_k is chosen
β	Parameter to tune between throughput and energy

D. State of the Art of Joint Scheduling and Power Control

In previous works on joint scheduling and power control [9], [10], [11], [18], the scheduling policy is to pack the maximum number of links that can be active simultaneously in each time slot. The objective is to maximize the spatial reuse of system resources and the throughput. Although the power control phase minimizes the transmission powers on the scheduled links, this scheduling policy does not take energy into consideration and thus may not be energy efficient.

Figure 1 shows an example of energy efficient joint scheduling and power control[2]. Given $\vec{b}$, the number of packets need to be transmitted and all feasible transmission scenarios and their related costs, there are three possible schedules that satisfy the $\vec{b}$ constraint:

1) Option 1: Choose S_1, S_3 and S_7. The transmission request is finished in three slots. The total energy cost is 7.56.
2) Option 2: Choose S_2, S_3 and S_6. The transmission request is also finished in three slots. The total energy cost is reduced to 6.2.
3) Option 3: Choose S_2, S_5, S_6 and S_7. The transmission request now is finished in four slots. The total energy cost is further reduced to 4.42.

This example shows that **the scheduling policy that maximizes the number of concurrent transmissions is not energy efficient** and suggests two ways to achieve energy efficient schedule:

1) Choose energy efficient combination of feasible transmission sets. In the example, compare option 2 to option 1, the combination of $S_2 + S_6$ is more energy efficient than $S_1 + S_7$. This is because the interference between link 1 and 4 is higher than the interference between link 1 and 5.
2) Tradeoff latency for energy efficiency. In the example, compare option 3 to option 2, S_3 is divided into $S_5 + S_7$. Instead of being scheduled simultaneously in one slot, link 2 and 5 are scheduled separately in two slots. Because of the elimination of interference, the total energy cost is further reduced.

To better understand the two approaches to save energy, figure 2(a) and 2(b) show two different schedules. Each column is a slot and each colored box represents an active link during that slot. The color of the boxes in a column indicates the the energy cost of the transmission set in that slot. Red color means high energy cost while green color means low energy cost. The meaning of β will be explained later. When $\beta = 0$, the transmission request is finished in less than 50 slots and many transmission sets have high energy cost. While in the schedule chosen by $\beta = 10$, the transmission request is finished in more than 70 slots. Even for two sets having the same number of active links, the energy cost of the set chosen by $\beta = 10$ has much lower energy cost compared to the set chosen by $\beta = 0$.

In the following sections, we will investigate two different problems of energy efficient joint scheduling and power control.

[2]The data is collected by simulations described in section V

III. TJSPC: Tunable Joint Scheduling and Power Control

A. Mathematical Formulation

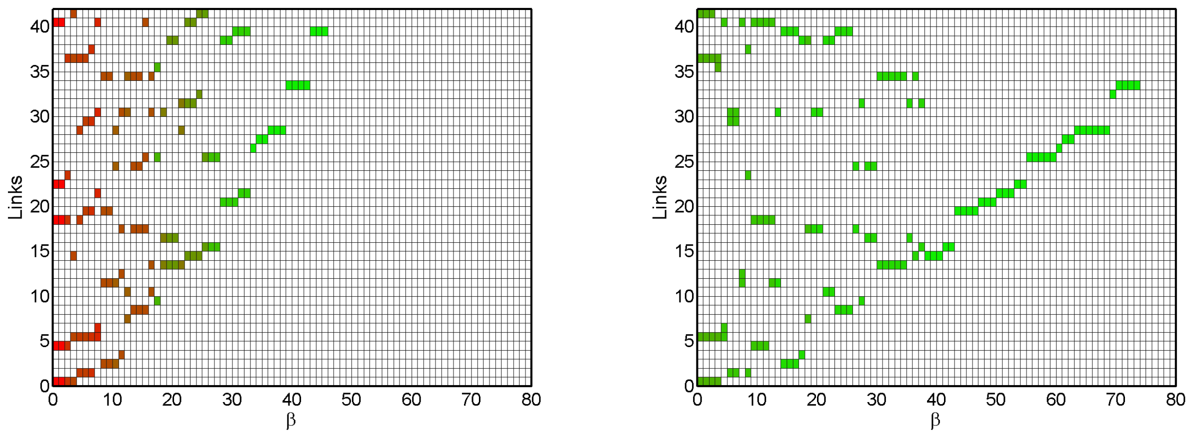
In this section, we will formulate the tunable joint scheduling and power control problem and show that prior works [9], [11] can be treated as special cases of our formulation. First we describe the notation used.

Assume that a TDMA time frame contains T slots. Here T models the per-hop delay tolerance of the application. The duration of a slot is normalized to 1. Let $b(e)$ denote the number of packets need to be sent on link $e = (i, j) \in E$ in a time frame. Denote $\vec{b}$ as a vector of size $|E|$ with each element corresponding to a link.

We denote S as the collection of all feasible transmission sets and $|S|$. Each feasible transmission set S_k is a vector of size E, with $S_k(e)$ equal to 1 if e is active in the set S_k. For each feasible set S_k, there is an energy cost $C_k = \sum_{S_k(e)=1}(P_e)$ which is the sum of the energy cost all active links in that set in a single slot. Here, P_e is the transmission power of link e from i to j. We ignore the reception power as it is almost constant regardless of the transmission power. Let $\vec{x}$ denote the solution, with x_k being the number of times that set S_k is chosen. The maximum number of sets allowed to be chosen is T.

The three important metrics of a sensor network system can be easily represented using the above parameters.

- **Energy**: The total communication energy cost in T slots: $\sum_k x_k C_k$.



(a) $\beta = 0$

(b) $\beta = 10$

Fig. 2. An example of two different schedules under $\beta = 0$ and $\beta = 10$.

- **Throughput**: We use the number of packets transmitted in T slots to represent the throughput. The number of slots that a link e is scheduled to be active is $\sum_k x_k S_k(e)$. However if a link is assigned a slot but there is no more packet to transmit, it is a waste of resource and should not be counted. So the actual number of packet a link e transmits is $max(\sum_k x_k S_k(e), \vec{b}(e))$ The total number of packets transmitted by all links is then: $\sum_{e \in E} max(\sum_k x_k S_k(e), \vec{b}(e))$.
- **Latency**: T is the worst per-hop latency of a packet if it is transmitted. A smaller T means that a packet need to be transmitted in a shorter time frame, and hence a smaller per-hop delay.

It is clear that it is not possible to optimize these three metrics simultaneously. Depending on the application requirements, different tradeoff strategies may be used. Some applications may need all transmission requests be satisfied before the deadline, while others may tolerate a certain number of packet drops. We will study the energy cost minimizing problem subject to transmission request guarantee in section IV. In this section we first form a problem that allows the applications to choose different tradeoffs among energy, latency and throughput.

Problem TJSPC:

$$\begin{aligned} \max\ gain &= \alpha \sum_{e \in E} max(\sum_k x_k S_k(e), \vec{b}(e)) \\ &\quad -\beta \sum_k x_k C_k \\ \text{s.t.} \sum_k x_k &\leq T \end{aligned} \tag{5}$$

By tuning α, β and T, we can achieve different tradeoffs between throughput and energy given the latency constraint. Specially, if α is 0, the problem is reduced to minimizing energy consumption with no constraint on throughput. Then the policy of the scheduling algorithm is to always search the set with minimum energy cost. If β is 0, the problem is reduced to maximizing throughput with no constraint on energy consumption. Then the objective of the scheduling algorithm is to maximize the throughput, same as previous scheduling algorithms[9], [11]. Without loss of generality, we will assume $\alpha = 1$ in the following discussion. As β increases, to maximize the gain it is better to choose transmission scenario with less energy cost. So the application can increase β when it is more interested in saving energy and decrease β when the throughput is a more important metric. The choice of T would be based on application-specific worst hop-to-hop latency requirements.

As β increases, the solution tends to choose transmission sets with smaller energy cost. However, to prevent a transmission set from being chosen because of its low energy cost even if it does not contribute any throughput, there should be an upper bound for β. Let $C_{min} = \min_k C_k$ and $C_{max} = \max_{k, |S_k|=1} C_k$. It is easy to see that to guarantee that a transmission set that can at least contribute 1 to the throughput is preferable to the set with minimum cost, we have:

$$-C_{min} < 1 - \beta C_{max} \Rightarrow \beta < \frac{1}{C_{max} - C_{min}} \tag{6}$$

This problem is NP-hard as it can be easily reduced from the Maximum Coverage problem [17]. However based on the fast greedy heuristic algorithm with constant factor approximation in [17], we propose greedy based heuristic algorithms and evaluate the performance by simulations.

B. Heuristic Approaches

1) Exponential Complexity Greedy Approximation: In this section, we present a greedy algorithm that has a constant factor approximation to the optimum solution. Given the collection of all feasible transmission sets S, the greedy algorithm selects T transmission sets by iteratively choosing the set that maximize the total $gain$ (defined in problem TJSPC) of the already chosen sets plus the current chosen set. We denote this algorithm as Greedy.

The greedy heuristic can be proved to be a $(1-\frac{1}{e})$-approximation algorithm.

Proposition 1: $wt(\vec{x}) \geq [1-(1-\frac{1}{k})^k]wt(OPT) > (1-\frac{1}{e})wt(OPT)$

This follows from the LEMMA 3.13 in [17]. For completeness, we show the proof in Appendix VIII.

When β is 0, to maximize the gain, the greedy algorithm will choose a feasible transmission set which can maximize the throughput, which leads to the solution to choose the set with maximum concurrent transmission. This is exactly the scheduling algorithm in [9], [11].

The complexity of the greedy algorithm is upper-bounded by $O(T|S|)$. A loose upper bound on $|S|$ is 2^E, which means that the complexity of the algorithm is exponential to the number of links. With the feasibility constraint, $|S|$ can be greatly reduced. Cluster hierarchical structures which have been proposed widely for wireless sensor networks (e.g. in [15], [16]) can further reduce $|S|$. Since cluster size are chosen to accommodate event monitor range, it is expected that at any time if an event happens, most of the time only one cluster may need to be active. Each cluster only schedules its own data transmission while treating interference from other clusters as ambient noise. Interference from clusters far away is negligible. Because only links within one cluster need to be considered, the number of feasible transmission sets is reduced considerably. We can further limit the maximum number of concurrent transmission links to a small number k, since in practice as it is difficult to sustain a large number of simultaneously active links in a given region. In this case, the number of feasible sets is upper bounded by 2^{k+1}.

Even $|S|$ can be reduced, the greedy algorithm needs to compute all possible transmission sets S and their energy cost in advance and has an exponential complexity of $O(T|S|)$ whenever the wireless channel condition changes, which makes it infeasible for practical use. However, it could be used as a framework or offline algorithm to give good insight on the performance of the network. In the next section, based on the greedy approximation algorithm, we propose a greedy based heuristic which does not need to pre-compute all feasible transmission sets with polynomial complexity.

2) Polynomial Greedy Heuristic: Assume that the link gain α_{ij} changes slowly compared to time frame T, the nodes need only to collect such information until a significant change of α_{ij} happens. The parameters can also be updated incrementally. Therefore, we assume α_{ij} is available in each node. Secondly, at the beginning of each time frame, source nodes will generate a control packet that contains the number of packets intended to its receivers. Therefore all source nodes are aware of $\vec{b}$. We assume the control packet is smaller compared to the data packet and the overhead is small. We will not discuss the details of the control message exchange protocol here.

Given a transmission scenario, a source node first check whether it is feasible. If it is infeasible, a link with minimum SNR or *Maximum Interference to Minimum Signal Ratio(MIMSR)* [11] is deferred. Then the new transmission scenario is checked again. Previous scheduling algorithms will stop once an feasible transmission set is found. The proposed algorithm, however, continues to search for a transmission set that can maximize the gain. Suppose the first admissible set is S_k, it will continue to drop the link with maximum MIMSR until there is only one active link. Suppose the following transmission sets the node gets are $S_{k1}, S_{k2}, ..., S_{kn}$. It is clear all these transmission sets are still feasible and $S_k \supset S_{k1} ... \supset S_{kn}$. For each feasible set S_{ki}, the node computes the related gains by $\alpha \sum_{e\in E} max(\sum_k x_k S_k(e), \vec{b}(e)) - \beta \sum_k x_k C_k$. Then the transmission set with the maximum gain is chosen and $\vec{b}$ is updated. The whole process is repeated again until either $\vec{b} = 0$ or T sets are chosen. We denotes the algorithm as DiGreedy.

Algorithm *DiGreedy*

Collect $\vec{b}$.
for $i \leftarrow 1$ **to** T
  $m \leftarrow$number of unzero element in $\vec{b}$
  $S(e) \leftarrow 1$ if $b(e) \geq 1$
  for $j \leftarrow m$ **to** 1
    Run power control algorithm for S
    $gain \leftarrow \alpha \sum_{e\in E} max(\sum_k x_k S_k(e), \vec{b}(e))$
    $-\beta \sum_k x_k C_k$ if S is feasible
    defer the link k with MIMSR
    $S(k) \leftarrow 0$
  Select the feasible transmission set S with maximum $gain$
  $\vec{b} \leftarrow (\vec{b} - S)$
  if $\vec{b} == \vec{0}$
    break;

The proposed DiGreedy algorithm has a complexity of $O(T|E|)$ which is polynomial to the number of links. However, unlike the greedy algorithm which always choose the transmission scenario that maximizes $\alpha \sum_{e\in E} max(\sum_k x_k S_k(e), \vec{b}(e)) - \beta \sum_k x_k C_k$ from all possible transmission sets, the DiGreedy algorithm only choose one from the transmission sets that are obtained by deferring the MIMSR link one by one. Therefore, it does not necessarily guarantee a $(1-\frac{1}{e})$-approximation to the optimal solution. However it is practically implementable and we will show by simulations that it achieves comparable performance to the greedy algorithm.

IV. JSPC-TR: Joint Scheduling and Power Control with Transmission Request Constraint

A. Problem Formulation

In TJSPC, we investigate the tradeoffs between throughput and energy efficiency. However, some applications may require all the transmission requests be satisfied. So in this section, we study the problem of joint scheduling and power control with transmission request constraint (JSPC-TR): Given a transmission request, minimize the energy cost subject to the constraint that all transmission requests are satisfied within the latency bound:

Problem JSPC-TR:

$$\begin{aligned} \min \quad & \textstyle\sum_k x_k C_k \\ \text{s.t.} \quad & \textstyle\sum_k x_k S_k(e) \geq b(e), \ \forall e \end{aligned}$$

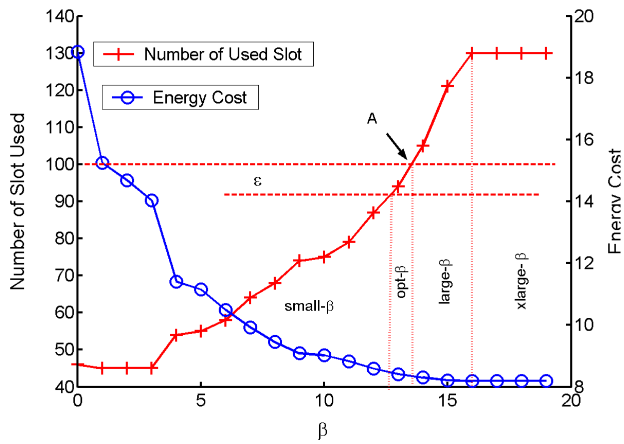


Fig. 3. The four characteristic regions in the number of used slot, energy vs. β.

$$\sum_k x_k \le T \tag{7}$$

This is still a NP-hard problem as it can also be reduced from the maximum coverage problem. Even the scheduling policy which always schedules maximum number of concurrent transmissions in each slot can not guarantee all transmission requests be satisfied. However, here we assume that the traffic load of the transmission requests are relatively low compared to the capacity of the network so that at least the scheduling policy that maximizes the concurrent transmissions can schedule all transmission requests in T slots.

We leverage the heuristic solution of problem TJSPC to solve JSPC-TR. First consider the following problem:

$$\begin{aligned} \max\ gain = &\ \textstyle\sum_{e\in E} max(\sum_k x_k S_k(e), \vec{b}(e)) \\ &-\beta \frac{\sum_k x_k C_k}{\sum_{e\in E} max(\sum_k x_k S_k(e), \vec{b}(e))} \\ \text{s.t.} &\ \textstyle\sum_k x_k S_k(e) \ge b(e),\ \forall e \end{aligned} \tag{8}$$

In contrast to TJSPC, there are two differences. First since the transmission requests have to be satisfied, to minimize the energy cost, we need to choose more energy efficient sets. So we change the energy metric to energy efficiency metric which is the average cost of sending one packet. Second, there is no constraint on the total number of slots but the transmission request. This problem can be solved using the same greedy algorithm for TJSPC. Suppose for each β, the solution is $\vec{x}^\beta$. Define $E(\beta) = \sum_k x_k^\beta C_k$. Then we need to find an optimum β that has the minimum energy cost:

$$\begin{aligned} E' : &\min_\beta E(\beta) \\ \text{s.t.} &\ \textstyle\sum_k x_k^\beta \le T \end{aligned} \tag{9}$$

Suppose β^* is the optimum β, then $\vec{x}^{\beta^*}$ is the heuristic solution to JSPC-TR. In next section, we discuss the algorithm to find the optimum β^*.

B. β^*-search Algorithm

Generally, as β increases, equation 8 tends to find solutions that are more energy efficient thus $E(\beta)$ decreases. Theoretically, $E(\beta)$ is not a monotonically decreasing function. However, in all the simulations, we see a clearly decreasing trend. Therefore, heuristically, we will assume $E(\beta)$ is a decreasing function.

Consider a typical curve in Figure 3 [3] which shows the energy and number of slots used to transmit a transmission request. Let $T = 100$, so transmission request should be finished in 100 slots. As shown in the energy curve, the energy cost reduces as β increases, however at the same time, the number of used slots also increase. The optimum operation point is point A in which exactly 100 slots are used and the energy cost is minimized. For practical purpose, we define a tolerance zone of width ϵ, as shown in Figure 3. Here, ϵ is a protocol parameter that determine the converge rate of the protocol which we will show later. We denote u as the number of used slots. The number of packets need to be transmitted in a transmission request $\vec{b}$ is $N = \sum_k \vec{b}(k)$.

From figure 3, we identify four characteristic operation regions(bounded by dotted line):

- small-β: $u < T - \epsilon$. In this sate, transmission requests are satisfied within T slots. The energy cost is high. It is clear that in order to reduce the energy cost, we need to increase β. However, this reduction must be performed carefully so that the transmission request is always satisfied. Intuitively, we need to achieve a balance between saving energy and satisfying transmission request. By invoking the fact that the relationship of u vs. β, for $u < N$, is near linear, this prompts the use of the following increase strategy:
$$\beta_{i+1} = \frac{\beta_i}{2}(1 + \frac{u_i}{T})$$
We will show later that such an update policy can reduce the energy cost while guaranteeing the transmission request satisfaction.
- opt-β: $T - \epsilon \le u \le T$. In this state, the network is operating within ϵ tolerance of the optimal point, where transmission request is satisfied and energy cost is a slightly higher. Hence the β is left unchanged for the next frame:
$$\beta_{i+1} = \beta_i$$
- large-β: $T < u < N$. In this state, the network is operating in a region that not all transmission requests can be satisfied within T slots. It is clear that we need to decrease β aggressively. Since the relationship of u vs. β is near linear, we use a decrease strategy as follows:
$$\beta_{i+1} = \beta_i \frac{T}{u_i} \delta_1$$
We will show later by choosing $\delta_1 < 1$, we can guarantee that policy will converge to the opt-β region.
- xlarge-β: $u \ge N$. In this sate, in all time slots, only one link is active. This consumes the least energy, however transmission request can not be satisfied within T slots when $T < N$. It is clear we need to decrease β aggressively. However in this region, u and β is no longer linear and we have no idea how large β is now. In order

[3] The figure is obtained by simulations discussed in section V.

$N = \sum_e \vec{b}(e)$
Solve JSPC-TR using equation 8 with β
if $u < T - \epsilon$ /*State is small-β*/
$\beta = \frac{\beta}{2}(1 + \frac{u}{T})$
else if $T - \epsilon \leq u \leq T$ /*State is opt-β*/
$\beta = \beta$
else if $T < u < N$ /*State is large-β*/
$\beta = \beta \frac{T}{u} \delta_1$
else if $T \geq N$ /*State is xlarge-β*/
$\beta = \beta \frac{T}{u} \delta_2$
end

Fig. 4. JSPC-TR protocol and β^*-search algorithm.

to converge to opt-β region and guarantee transmission request, β need to be decreased more aggressively than in the region of large-β:

$$\beta_{i+1} = \beta_i \frac{T}{u_i} \delta_2$$

with $\delta_2 \leq \delta_1$.

We will show in next subsection that starting from any region, the above β^*-search algorithm converges to opt-β region.

The entire JSPC-TR protocol is summarized in figure 4. The basic process is following: at a TDMA time frame, under the current β and transmission request, the scheduler decides the state of the network then adjusts β according to the β^*-search algorithm. The updated β is then used for next TDMA frame. Here we assume the traffic requests change slowly compared to the converge rate of the β^*-search algorithm.

C. Analysis

First we present some analysis of the β^*-searching algorithm. Under the assumption of linear relationship of u vs. β in small-β region/state, we are able to prove that network will converge to the opt-β state. Another assumption is that the traffic load in TDMA frame does not change abruptly. The proof is similar to the one used in [20].

Proposition 2: Starting from small-β, with linear relationship between u and β, the state will remain small-β until it converges to opt-β in $\lceil \frac{u_0 - 1}{\epsilon} \rceil$ iterations.

Proof: Suppose the linear behavior for $u < T - \epsilon$ is $u = a\beta$ and $u_i < T - \epsilon$. So the β is increased by:

$$\beta_{i+1} = \frac{\beta_i}{2}(1 + \frac{T}{u_i})$$

Thus,

$$u_{i+1} = \frac{u_i}{2}(1 + \frac{T}{u_i}) = \frac{u_i + T}{2}$$

Since $\beta_{i+1} > \beta_i$, the next state can either be small-β, opt-β, large-β or xlarge-β. Suppose the next state is neither small-β nor opt-$beta$, then $u_{i+1} > T$. Then,

$$u_{i+1} = \frac{u_i + T}{2} > T$$

Hence, $u_i > T$. However this contradicts with $u_i < T - \epsilon$ since the starting state is small-β. Thus, the state can only be small-β before it reaches opt-β.

Now we prove that the converge takes $\lceil \frac{u_0 - 1}{\epsilon} \rceil$ iterations. Let j be the first one when the network is in opt-β state.

$$\begin{aligned} u_j &= \frac{u_{j-1} + T}{2} > T - \epsilon \\ u_{j-1} &= \frac{u_{j-2} + T}{2} > T - 2\epsilon \\ &\vdots \\ u_1 &= \frac{u_0 + T}{2} > T - 2^{j-1}\epsilon \end{aligned}$$

Thus, it takes $j > log_2(\frac{u_0 - 1}{2})$ iterates before $u_j > T - \epsilon$. In the whole process, the transmission request is always guaranteed. ∎

Proposition 3: Starting from large-β or xlarge-β, the state will converge to opt-β.

Proof: Suppose the linear behavior for $u < T - \epsilon$ is $u = a\beta$. For large-$beta$ state, $u > T$. So β is decreased by:

$$\beta_{i+1} = \beta_i \frac{T}{u_i} \delta_1 = \beta_0 \frac{T^i}{\prod_{k=0}^{i} u_k} \delta_1^i$$

Since $\delta_1 < 1$ and $u_k > T$, β will keep decreasing until it change to either opt-β region or small-β region which will converge to opt-β by Lemma 2.

Similarly, starting from xlarge-β, the network can also converge to opt-β. ∎

V. Simulation Results

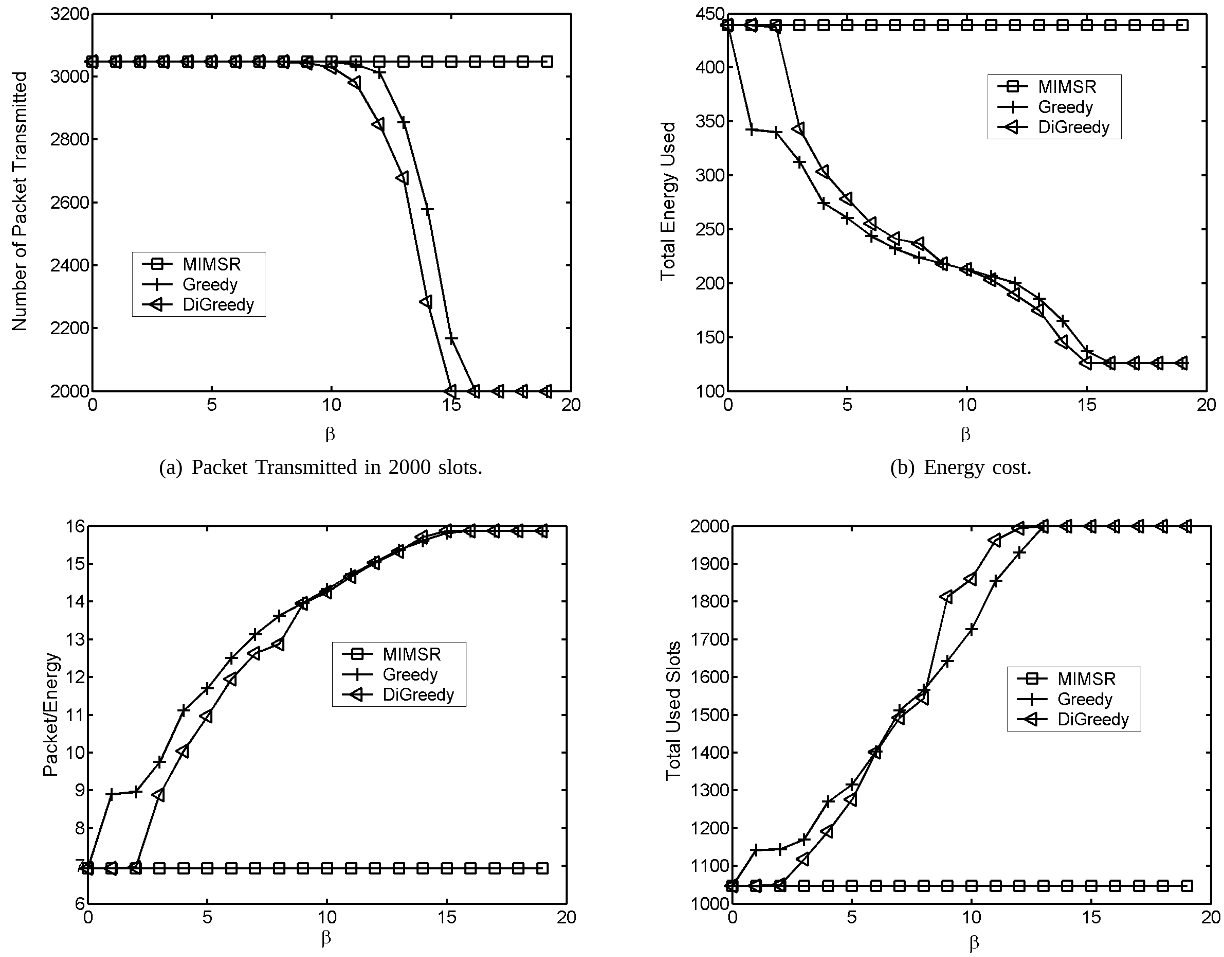
We simulate the performance of the algorithms for a stationary network consisting of a grid of 49 nodes. The distance between adjacent nodes is set to 20 meter. The radio parameters are set according to the CC1000 radio used in Mote MICA2 [21], [22]. The minimum transmission power is $P_{min} = -20dBm$ and the maximum transmission power is $P_{max} = 5dBm$. According to [19], The path loss factor in a typical outdoor environment is 4 and the noise floor is around $-105dBm$. The SNR threshold γ for successfully packet reception is set to be $10dB$. We choose 42 links and pre-computed all feasible transmission sets and their energy costs. The maximum number of active links in a transmission scenario is 5.

A. Simulation Results for TJSPC

Besides the Greedy and DiGreedy algorithms, we also simulate the scheduling algorithm (referred as MIMSR) proposed in [11]. We simulated 20 time frames which consist of T slots. Each node randomly generates 1 to 6 packets to be transmitted in each time frame. All results are averaged over 10 seeds. From the simulations, we learned three key lessons, described below.

Lesson 1: By relaxing the latency bound, we can get significant energy savings[4]. In the simulation, we fix the traffic load while increasing the latency bound T. Figure 5 shows the impact of T on the energy cost performance of the algorithms.

[4]The unit of energy is 12.7τ mJ, where τ is the transmission time of one packet



(a) Packet Transmitted in 2000 slots.

(b) Energy cost.

(c) Energy efficiency in terms of number of packets transmitted per unit of energy.

(d) Total used slots for delivered packet.

Fig. 6. Performance of MIMSR, Greedy and DiGreedy as a function of β with $T = 100$.

The packet reception ratio (which is directly proportional to the throughput) remains above 95% for all T and β. Larger β can be used for higher latency bound because preference can be given to feasible transmission set with smaller energy cost. As T increases, the energy cost of Greedy and DiGreedy decreases significantly. Compared to MIMSR which remains around 435 regardless of β, the savings can be as high as 50%.

Figure 6(d) shows that total number of used slots for the algorithms with the same traffic load and fixed $T = 100$. As MIMSR always schedules the maximal feasible set, it uses less slots in transmitting the traffic. However, by increasing β, Greedy and DiGreedy would give higher and higher preference on low energy cost transmission sets, thus increase the number of slots used. The more slots used means more packets will be transmitted at the end of a time frame, thus a higher average latency, but still within the latency bound.

Go back to figure 2(a) and 2(b) which show the schedules computed by $\beta = 0$ and $\beta = 10$ separately. Clearly $\beta = 10$ is able to choose more energy efficient transmission sets.

Lesson 2: By varying β, the algorithm is able to save significant energy without hurting throughput. Figure 6(a) and 6(b) shows the number of packets delivered and the total energy cost in 20 frames which consists of 100 slots respectively. When $\beta \leq 10$, Greedy and DiGreedy can deliver almost same number of packets. The energy cost decreases as β increases even though the number of packets delivered is the same. The energy savings can be as much as 50%. This shows the algorithms' ability to choose a better combination of transmission scenarios. When $\beta > 10$, the number of packets delivered by Greedy and DiGreedy begins to decrease. When $\beta > 15$, the algorithms will always choose the transmission scenario with only one link active that is most energy efficient. Thus the total number of packets can be delivered in 2000 slots remains 2000. Figure 6(c) shows the energy efficiency in terms of the number of packets delivered in units of energy. Clearly as β increases, the energy efficiency of the scheduled set increases.

Lesson 3: DiGreedy algorithm has comparable performance to the Greedy approximation algorithm. For all the simulations, Greedy and DiGreedy can save more energy than MIMSR while maintaining relatively same throughput or at a little sacrifice of the throughput. As we can see from all figures, DiGreedy, as a heuristic solution with no approximation guarantee, has almost the same performance as

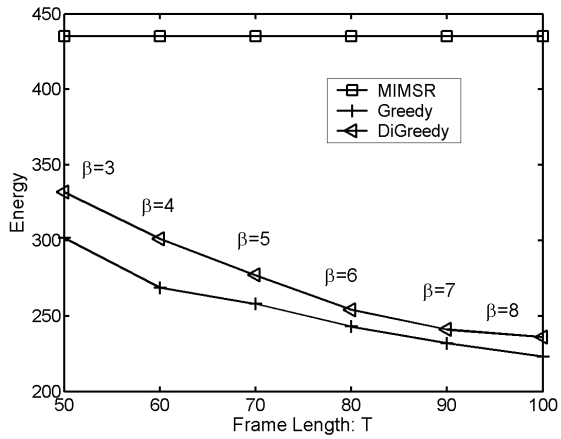


Fig. 5. Energy cost reduces as latency constraint increases as a function of T with varying β.

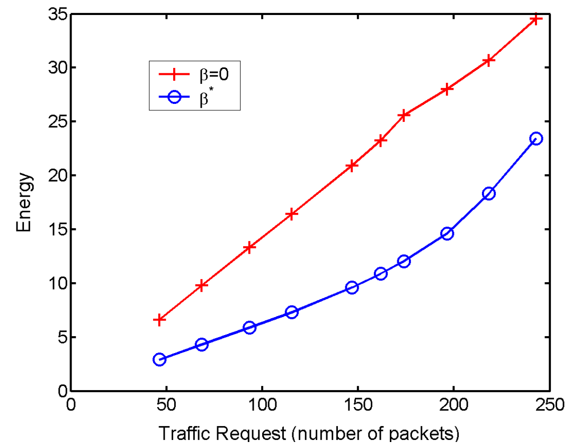


Fig. 8. The energy cost under different traffic request load.

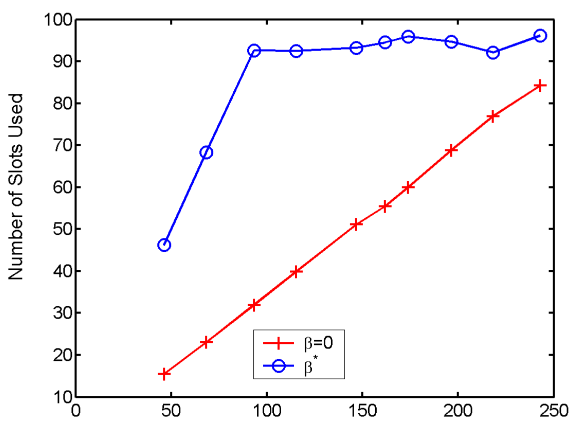


Fig. 7. The number of slots used under different traffic request load.

the Greedy which is $(1 - \frac{1}{e}$ approximate to the optimization solution.

B. Simulation Results for JSPC-TR

We simulated the β^*-searching algorithm under various traffic load requests to find the β^*. Then we compared the performance of two different schedules computed by $\beta = 0$ and β^*. All results are averaged over 10 seeds. In the simulation, $\delta_1 = \delta_2 = 0.8$ and $\epsilon = 10$.

Figure 7 and 8 show the number of slots and energy used to finish the transmission request under different traffic load separately. Under all traffic load request, our algorithm is able to operate in opt-β region and thus consume much less energy while all transmission requests are satisfied within $T = 100$ slots. The number of used slots by β^* are always between 90 and 100, except for very low traffic load when the number of packets is less than 100.

VI. Related works

Recently there have been several works ([9], [11], [12], [13], [14]) on jointly scheduling and power control in wireless sensor networks. In the following, we discuss in detail about those works as they are closely related to our work.

ElBatt and Ephremides [9], [10] considers the problem of joint scheduling and power control in multi-hop networks. Their solution has two alternating phases: scheduling and power control. A transmission scenario (the selection of a particular set of links to transmit data) is defined as valid if no node is to transmit and receive simultaneously and no node is to receive from more than one neighbor at the same time. An admissible transmission scenario means that a set of transmission power is available to satisfy the SNR constraints for all links in the scenario. In each slot the scheduling algorithm first search a maximum valid scenario, which then is verified by the distributed power control algorithm to see if it is admissible. If the valid scenario is not admissible, the scheduling algorithm drops the link with minimum SNR and the power control algorithm is rerun. Once an admissible transmission scenario is found, the sources will transmit data packets using the computed transmission powers in current slot.

The authors in [11] proposed a distributed joint scheduling and power control algorithm for multicasting in wireless Ad Hoc Networks. As in [9], the algorithm in [11] also tries to schedule all links with data transmission requirement and only defer the link with Maximum Interference to Minimum Signal Ratio (MIMSR) until a feasible power control solution is available. In both [9] and [11], while the power control algorithm is optimal in mimizing the transmission power of a single transmission scenario, the scheduling algorithm which tries to find a maximum valid scenario may result in a non-optimal solution in terms of total energy consumption in multiple slots.

Bhatia and Kodialam [12] derive a performance guaranteed polynomial approximation algorithm for jointly solving routing, scheduling and power control. However, they consider a slightly different interference model in which the SINR level impacts the average rate rather than the success or loss of individual packets. (In our paper, as in [9], [11], we will assume an interference model in which a radio can either successfully receive a packet or not depending on the $SINR$

threshold). A closely related work by Cruz and Santhanam [13] proposed a joint scheduling and power control algorithm to minimize the total average transmission power in the wireless multi-hop network, subject to the constraints on average data rate per link and peak transmission power per node.

The authors in [18] consider the problem of power controlled minimum frame length scheduling for TDMA wireless networks. Given a set of one-hop transmission requests, their objective is to schedule them in a minimum number of time slots. The consider per-slot and per-frame versions of the problem and develop mixed integer linear programming models. To minimize the frame length, their approach is to schedule the maximal feasible active links in each slots, same as [9], [10].

VII. Conclusion

In this paper, we studied the fundamental energy efficiency problem of joint TDMA link scheduling and power control in wireless sensor networks. We found that different transmission scenario can have significantly different total transmission powers. By carefully choosing different combinations of feasible transmission scenarios in multiple slots, the total energy costs can be reduced. This improves energy efficiency compared to previously proposed joint scheduling and power control algorithms, which always try to schedule maximum concurrent transmissions.

We formulated a joint link scheduling and power control problem that aims to maximize a function of throughput and energy cost subject to latency constraint(TJPSPC). This formulation allows a tunable performance tradeoffs between throughput, latency and total energy cost. We showed this NP-hard problem formulation can be solved using a greedy algorithm which is an $(1-\frac{1}{e})$-approximation to the optimal solution with exponential approximation. We then presented DiGreedy, a heuristic greedy algorithm with polynomial complexity. Simulation results show that DiGreedy algorithm has similar performance to the greedy algorithm, and can achieve significant energy savings at no or little sacrifice of the throughput. We also investigated the joint scheduling and power control problem with constraint on the number of packets to be sent on each link. We leverage the heuristics for TJSPC to solve this problem by using the optimum β which achieves energy efficiency while guaranteeing the satisfaction of transmission requests. Simulation results show 50% energy savings can be achieved without sacrificing throughput.

VIII. Acknowledgements

We would like to thank Yang Yu for his valuable input on this work and acknowledge his assistance in the problem formulation. This work is supported in part through NSF research grants numbered CNS-0325875, CNS-0347621, CNS-0435505, and CCF-0430061.

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IX. Appendix

Proposition 4: $wt(\vec{x}) \geq [1-(1-\frac{1}{k}^k]wt(OPT) > (1-\frac{1}{e})wt(OPT)$

Proof: Suppose $\vec{x}^i$ is the greedy solution in the first i slots, let

$$G_i = \sum_k x_k^i S_k$$

and

$$wt(G_i) = \sum_e max(\sum_k x_k^i S_k, \vec{b}(e)) - \beta \sum_k x_k^i c_k$$

Suppose in $i+1$ slot, transmission set S_j is chosen, Then $x_j^{i+1} = x_j^i + 1$ and $G_{i+1} = G_i \cup S_j$, we have:

$$wt(G_{i+1}) = \sum_e max(\sum_k x_k^{i+1} S_k, \vec{b}(e)) - \beta \sum_k x_k^{i+1} c_k$$

Now, the gain of the first selceted $(i-1)$ sets is $wt(G_{i-1})$. The difference between $wt(G_{i-1})$ to the gain of the optimal solution is $wt(OPT)-wt(G_{i-1})$. Then at least $wt(OPT)-wt(G_{i-1})$ worth of gain not covered by the first $(i-1)$ sets are covered by the T sets of OPT. By the pigeonhole principle, one of the T sets in the optimal solution must cover at least $\frac{wt(OPT)-wt(G_{i-1})}{T}$ worth of gain. Since S_j is a set that achieves maximum additional gain, it must also cover at least $\frac{wt(OPT)-wt(G_{i-1})}{T}$. That is:

$$wt(G_i)-wt(G_{i-1}) \geq \frac{wt(OPT)-wt(G_{i-1})}{T}$$

Now let us suppose for $i=1$, $wt(G_1) \geq \frac{wt(opt)}{T}$, then,

$$\begin{aligned}
wt(G_{i+1}) &= wt(G_i)+(wt(G_{i+1})-wt(G_i)) \\
&\geq wt(G_i)+\frac{wt(OPT)-wt(G_i)}{T} \\
&= (1-\frac{1}{T})wt(G_i)+\frac{wt(OPT)}{T} \\
&\geq (1-\frac{1}{T})(1-(1-\frac{1}{T})^i)wt(OPT)+\frac{wt(OPT)}{T} \\
&= (1-(1-\frac{1}{T})^{i+1})wt(OPT) \\
&> (1-\frac{1}{e})wt(OPT)
\end{aligned}$$

■