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EXPLOITING BOOTY IN WIRELESS COMPLEXES WITH VIGOR AND SCHEDULING CONSTRICTIONS FOR INTERVALLIC DATA RIVULETS

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Abstract — Power efficiency is an important design issue in mobile devices. A transmitter communicates with multiple receivers periodically. Each packet is associated with a delay constraint. The data streams have different importance levels, power functions, and levels of data sizes. The objective is to develop the transmit data streams of different data sizes at different transmission rates so that the system reward can be maximized under given time and energy constraints. To develop a dynamic programming algorithm for the optimal solution in pseudo polynomial time. A fast polynomial-time heuristic approach based on clustering of states in state space is presented to achieve close approximation. Simulation results demonstrate the effectiveness of the optimal solution and the polynomial-time approach can achieve near-optimal results.

Keywords — Reward maximization, power-aware packet scheduling, wireless networks, embedded systems.

I. INTRODUCTION

ENERGY is a critical resource of wireless devices powered by battery with limited capacity. Reliable content delivery over a wireless channel is a major source of energy expenditure. The energy expenditure for the transmission rate with proper wireless channel coding or modulation schemes . As applications are usually delay-sensitive, packet delivery delays should be allowed only if it is controllable. Different delay constraints were investigated in energy-efficient packet transmission such as average delay, a common deadline to all packets and individual deadlines .Most existing work focus on the minimization of the total energy consumption under the timing constraints. Wireless nodes powered by these energy sources are subjected to limited amount of energy which is collected in each period. Due to the limitation in both delay and energy, it is often impossible for a wireless node to deliver all data in the transmission buffer at a time. Instead, the node tends to transmit data collected in the buffer selectively under time and energy constraints. The periodic data streams destined to different receivers may consume different amount of energy. These data streams may also have different importance. Take image sensing for example, the wireless node may support several formats with different amount of information, such as in raw data format or compressed formats in jpeg and jpeg. With a larger data size, more information can be conveyed. When a wireless node cannot send all of its data, it is more desirable to transmit more valuable data first. To quantify the level of importance of a packet, we associate a reward to each packet transmitted. The objective is to maximize system rewards under given time and energy constraints. Wang Mandayam tried to maximize system throughput and the probability of successful file transmission. They considered a transmitter that could operate only in two states: either an active state or an idle power state. The reward maximization problems for packets with individual energy and delay constraints. We consider a general scenario in which a wireless node communicates with multiple receivers periodically over an AWGN channel. As the receivers may have different distances to the sender, they may require different amount of power under the same data transmission rates. Each data stream has several discrete data size levels and can be transmitted at different transmission rate levels. The contributions of work are two folds. First, we propose the optimal solution to the time and energy constrained reward maximization problem. We show that the reward optimization problem for periodic data streams with discrete data sizes and transmission rate levels is NP-hard. We develop a dynamic programming algorithm to solve the problem optimally in pseudo polynomial running time.

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II. SYSTEM MODEL AND PROBLEM FORMULATION

To define data and energy consumption models for the reward maximization problem. Then, we present a formulation of the reward maximization problem under given time and energy constraints.

1) Data Model

The energy-efficient problem in wireless networks were largely targeted at communication channels over a single-transmitter-single-receiver model. A single-transmitter-single-receiver model is also known as point-to-point communication. Where there is only one transmitter will communicate with a single receiver. In recent years, generally single transmitter- multiple-receiver model in which a wireless transmitter

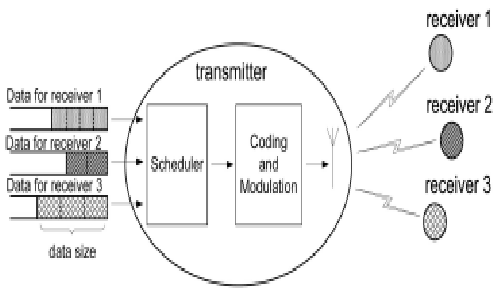

Figure : 1 - Single-transmitter-multiple-receiver model in a single-hop wireless network

Communicates with multiple receivers periodically. In this model, the transmitter can only communicate with one receiver at a time and has an energy budget in each transmit cycle. Each receiver will receive data from the transmitter periodically. Every transmitter-receiver pair has a maximal amount of data to be transmitted in each time period. The receivers are located with different distances from the transmitter. The data to different receivers can be transmitted at different transmission rates.

2) Power Consumption Model

The power consumption of a wireless transmitter can be divided into two parts: circuit power and transmission power. The transmission power usually long-range communications (over 100 m) are common in wireless networks. In order to maintain the same transmission rate, the required transmission power needs to increase with the distance between the transmitter-receiver pair to offset the propagation loss. The circuit power is expected to decrease as the IC technology advances. This part of power only occupies a small portion of the whole power consumption., we assume the transmission power dominates the negligible circuit power. In power model, we assume the channel is slowly time-varying, which means the channel condition will not change during transmission. Proper channel coding can reduce the energy consumption effectively during transmission.

We take the AWGN channel model as an example, which explains how energy, rate, and data size are related. With optimal channel coding, the maximum transmission rate

$$S = \frac{B}{2}\log_2\left(1 + \frac{P'}{N_0 B}\right),$$

s the transmission rate, P0 is the received signal power, N0 is the spectral density, and B is the channel bandwidth. From this equation, we can describe the relationship between the transmission rate S and the received power P0 by the following equation:

$$P' = N_0 B \cdot \left(2^{\frac{2S}{B}} - 1\right).$$

we aforementioned, the power will increase with distance between transmitter and receiver in order to maintain the same transmission rate. Considering this power attenuation, we have

$$P = \frac{P'}{A} = \frac{N_0 B}{A} \cdot \left(2^{\frac{2S}{B}} - 1\right),$$

where P is the transmission power and A is the attenuation factor for the transmitter-receiver pair. The attenuation factor A is generally inversely proportional to a function of the distance, denoted by l. For example, this function could be a square function, A / 1=l2. we do not assume any specific form of the relationship between attenuation factor and distance except that all transmitter receiver pairs have the same fading functions which are only affected by distance. It is easy to see that the required transmission power P is strictly increasing and strictly convex in the transmission rate S. This power function Pð SÞ is continuous in S though we only consider the discrete cases for this function in this paper.

Let Pi denote the power consumption function for task i. Let Ci and Si represent the size and rate of data transmission for _i, respectively. The transmission time to transmit data Cib units of energy. The energy consumed for _i for transmission in one period, denoted by Ei, with data size Ci at transmission rate Si becomes

$$E_i(C_i, S_i) = P_i(S_i)\frac{C_i}{S_i} = \frac{N_0 B}{A_i} \cdot \left(2^{\frac{2S_i}{B}} - 1\right) \cdot \frac{C_i}{S_i},$$

where the coefficient Ai for each transmitter/receiver pair differs depending on the distance between them. As the channel states and receiving nodes are assumed to be

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static during the transmission period, the power attenuator factor Ai is also static.

3) Problem Formulation

We consider the transmission in a hyper period T which is defined as the Least Common Multiple (LCM) of task periods T1; T2; . . . ; TN. The consideration of a hyper period ensures all tasks can finish their periodic transmissions at least once. Let Emax represent the units of energy budget allocated to the transmitter during this hyper period T .The objective is to maximize the total reward while all tasks meet their deadlines and the total energy consumption does not exceed the budget Emax. In the optimization problem has to find a speed and a data size for each task to maximize the overall rewards while satisfying delay and energy constraints.

III. DYNAMIC PROGRAMMING FOR THE OPTIMAL SOLUTIONS

A general method of solving the optimal MMKP problem is to search the solution space until an optimal solution is found and confirmed . We can use breadth-first search to generate partial solution along with the sequence of receivers. This algorithm enumerates all possible data sizes and transmission rate for each receiver. This process can be visualized as a state space branch where each non leaf node in this tree has M _ K children if there are M transmission rate levels and K data size levels for each receiver. Therefore, a naive algorithm would generate ðM _ KÞi nodes at level I . The state space can grow exponentially with the task number. To reach the solution in practical runtime, most researchers relied on heuristics to obtain approximated solutions or adapted approaches to reduce the computational complexity. These approaches are not readily applicable to our problem as our problem involves more decision factors. To develop a dynamic programming algorithm for the reward maximization optimization problem with two-dimension multiple choices of data size and transmission rate.

Algorithm1. Reward maximization using dynamic programming

$L_0 = \langle(0,0,0)\rangle$
for $i = 1$ to N **do**
  for all data size $j \in \{c_i^1, c_i^2, \ldots, c_i^K\}$ **do**
    for all transmission rate $k \in \{s_1, s_2, \ldots, s_M\}$ **do**
      $L'_{ijk} = L_{i-1} \oplus (\bar{r}_{ijk}, \bar{t}_{ijk}, \bar{e}_{ijk})$
    end for
  end for
  merge L'_{ijk} into a list L'_i in a decreasing order of reward
  delete all states in L'_i with $\bar{t} + \sum_{j=i+1}^{N} \frac{T}{T_j} \frac{C_j^{min}}{s_M} > T$ or $\bar{e} + \sum_{j=i+1}^{N} \frac{T}{T_j} E_i(s_1, C_j^{min}) > E_{max}$
  $L_i =$ Prune-Lists(L'_i)
end for
return the largest state in L_N

procedure Prune-Lists(L')
  $L'' = \emptyset$
  while $L' \neq \emptyset$ **do**
    choose and delete the largest state $(\bar{r}', \bar{t}', \bar{e}')$ from L'
    $flag = true$
    if $L'' == \emptyset$ **then**
      add $(\bar{r}', \bar{t}', \bar{e}')$ to the end of list L''
    else
      for all states $(\bar{r}'', \bar{t}'', \bar{e}'')$ in L'' **do**
        if $(\bar{t}'' < \bar{t}'$ and $\bar{e}'' \leq \bar{e}')$ or $(\bar{t}'' \leq \bar{t}'$ and $\bar{e}'' < \bar{e}')$ **then**
          $flag = false$
          break
        end if
      end for
      if $flag == true$ **then**
        add $(\bar{r}', \bar{t}', \bar{e}')$ to the end of list L''
      end if
    end if
  end while
  return L''
end procedure

IV. TIME-EFFICIENT APPROXIMATION

Although the above three pruning conditions are effective in removing unpromising states, the state space in Algorithm 1 can still expand significantly and it will be computationally expensive to get the optimal solution with a large number of receivers, data sizes, and transmission rates. In practice, it is not always necessary to find the optimal solution with limited time and computation resources. A near-optimal solution is more desirable if it can be completed in reasonable time while consuming reasonable computation resources. First propose a polynomial-time heuristic approach. Then, we will analyze the complexity of this algorithm.

4.1 Polynomial-Time Approximated Approach (Clustering)

We develop a heuristic algorithm, named Clustering algorithm, to approximate the optimal solution to the proposed problem with a polynomial computational time complexity. This Clustering algorithm is novel for the proposed problem. The general idea of this algorithm can be traced back to data clustering in mathematics. This Clustering algorithm is based on a clustering property of the final states after we enumerate all the tasks. If we plot the all of the final states after enumerating all possible combinations of data sizes and transmission rates into a 3D space with the coordinates of ðreward; energy; timeÞ. We can find the nodes, representing the final states, are clustered instead of randomly scattering. This is attributed to the discrete levels of data sizes and transmission rates. Those nodes in the same cluster tend to have close reward values, energy consumption, and transmission time.

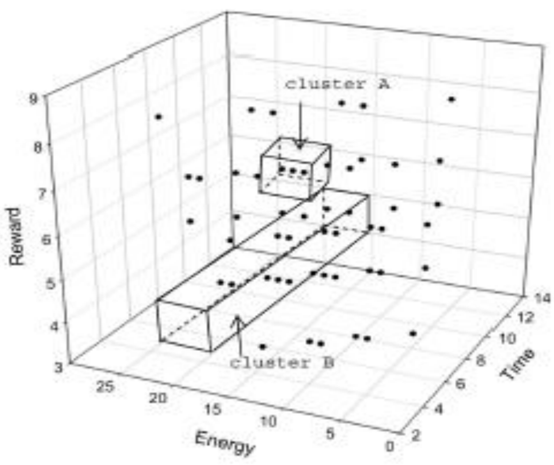


Figure : 2 - The reward-time-energy relationship in a 3D space

V. PERFORMANCE EVALUATION

We simulate the following four algorithms in our experiment:

Dynamic programming algorithm for optimal solution: We simulate this algorithm to obtain the optimal solution for reward maximization problem. . Polynomial-time Clustering algorithm (Clustering):

This is the proposed time-efficient Clustering algorithm for a near-optimal solution. Greedy-pack and greedy-unpack algorithms: These two algorithms are adapted from as the competitors of proposed polynomial-time Clustering algorithm. Though the reward maximization problem is different from that in our work, the method of designing heuristic approaches is a general principle and can still be adapted to the problem studied in this paper. We compare the solutions of Clustering, greedy-pack, and greedy-unpack with the optimal solution obtained by the dynamic programming algorithm. We use the metric of normalized system reward to show how close these algorithms can approximate the optimal solution. We study the effect of different parameters on the simulation results and investigate the execution time cost for different algorithms. We conduct simulations to show to what degree our proposed dynamic programming algorithm can restrict the explosion of state space. In addition, we Investigate the impact on approximation by choosing different numbers of clusters and strategies of representative node selection for Clustering algorithm.

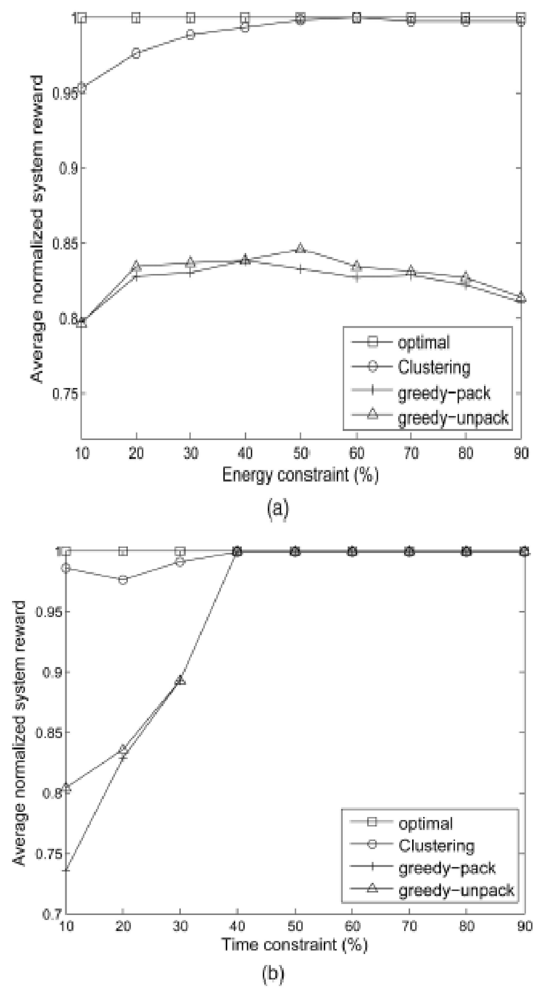
1) Simulation Setup

The wireless channel settings we used are similar to those described . The channel bandwidth is 1 MHz. The bits per transmission is set to be 1, 2, 4, and 6 bits/Hz (BPSK). Each receiver will receive data from the transmitter periodically at the above transmission rates. These periodic data streams are generated based on the following parameters: distance between receiver and transmitter, the number of different sizes of data to be transmitted, the sizes of data to be transmitted, period, and reward values. The distances between transmitter and receivers are uniformly distributed in a range of [20, 200] meters. Under this setup, a transmission power of 20 mW is required to reliably transmit data at 1 bit/Hz (BPSK) at a distance of 100 m. we can calculate the power consumption for different receivers with different transmission rates. We assumed the number of data size levels to be 5 for all receivers. The data sizes are uniformly distributed in the range of ½1; 16_ Mb. The periods for each receiver can be represented by the number of jobs transmitted to each receiver, denoted by fjob1; job2; . . . ; jobNg, within the time interval T. So the period Ti can be calculated as Ti ¼ T jobi.

The value of jobi is a random integer value in the range of [1, 12]. Based on the above parameters, we can calculate the energy consumptions by the energy function. i ; sMÞ. T is the multiplication of a parameter _ and , where 0 < _ < 1 and T is the total transmission time for all data streams to transmit the largest size of data at the smallest transmission rate . A lower value of _ means more stringent energy constraint and a lower value of _ means tighter deadline. We refer to _ and _ as energy constraint factor and time constraint factor, respectively. In Clustering algorithm, we assumed nbins ¼ mbins ¼ 10 _ N _ ðlogM þ logKÞ by default.

2) Simulation Results

In this part, we first study the impact of time and energy constraint factors on the performance of the four algorithms. Second, we investigate the relationship between the performance and execution time. Third, compared with our previous work. further study the effectiveness of our dynamic programming algorithm for optimal solution. Finally, we simulate our Clustering algorithm with different parameters to see the effect on the extent of the approximation to the optimal solution. Impact of Time and Energy Constraint Factors The first experiment is to study the impact of time and energy constraint factors on the performance. We simulated optimal, Clustering, greedy-pack, and greedy-unpack algorithms for this reward maximization problem with different time and energy constraint factors. The system reward normalized to the optimal value is presented . The below figure demonstrates the impact of energy constraint factor on the performance. We assumed the number of receivers to be 10 and the time constraint factor _ to be 0.2. We increased the energy constraint factor _ from 0.1 to 0.9 with a step size of 0.1. The normalized reward of Clustering increases with the increase of energy constraint factor. It is around 95 percent when _ ¼ 0:1 but can reach more than 99 percent when_ _ 0:5. The normalized rewards of two greedy algorithms always have a big gap larger than 15 percent from the optimal value even if the energy constraint is loose. The best normalized reward is bounded by 85 percent. Fig. 6b shows the impact of time constraint factor on the performance. We increased the time constraint factor _ from 0.1 to 0.9 with each step equal to 0.1 and assumed a constant task size of 10 receivers and a constant energy constraint factor _ ¼ 0:2. The results of Clustering are always larger than 95 percent. With a loose time constraint.



3) Impact of Number of Clusters for Clustering

In the Clustering approach, the size of state space depends on the number of clusters, which affects the accuracy of final result. In this part, we will study the impact of number of clusters on the performance for the Clustering algorithm. In all the simulations, we assume mbins ¼ nbins, and both the time and energy constraint factors to be 0.2. First, we study the impact of different number of clusters on the accuracy approaching optimal solution and time cost. We tune the value of n bins to be 50, 100, 200, 400, 800, which means the numbers of clusters can be 2,500, 10,000, 40,000, 160,000, 640,000. The number of receivers is increased from 5 to 30 with each step equal to 5. The impact of different number of clusters on both the accuracy and execution time of Clustering algorithm. We notice that both the normalized system reward and execution increase with the increase of cluster number . This is because larger number of clusters preserves more states in each iteration. So the states that can lead to optimal or near optimal solution will be more likely preserved for future search, which will lead to more execution time cost. More receivers lead to larger state space. This requires us to have a large enough number of clusters to get more precise solution.

VI. CONCLUSION

The reward maximization problem under time and energy constraints will be defind by using wireless network . Transmitting different periodic data streams to different receivers will consume different energy and produce different reward values. Each data stream has several levels of data sizes while the transmitter can deliver them at several levels of transmission rate. The objective is to maximize system reward under time and energy constraints by selecting a certain data size and a certain transmission rate for each data stream. The exact optimal solution is obtained by the dynamic programming algorithm. Instead of searching the optimal solution with tremendous costs, we propose time-efficient approximated approaches, including a polynomial-time heuristic approach and two greedy algorithms, to approximate the optimal solution closely at much lower cost. Simulation results demonstrate the effectiveness of the dynamic programming algorithm for exact optimal solution and the performance of the polynomial-time heuristic approach in approximating the optimal solution. The resource being allocated is usually power or bandwidth, and the quantity to be maximized is most often Shannon capacity.

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