Dynamic Programming-Based Antenna Resource Allocation Algorithm for Wireless Powered Sensor Networks

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***Abstract*—In a wireless powered sensor network (WPSN), wireless sensors can receive energy from energy transmitters for operation. To improve the performance of the WPSN, the multi-source wireless power transfer technique based on the beamforming multi-antenna architecture has emerged as an attractive solution. Thus, in this paper we consider the WPSN system which includes multiple wireless sensors and multiple multi-antenna energy transmitters. We proposed a dynamic programming-based antenna resource allocation algorithm, which takes the diverse distances among various energy transmitting antennas into account, for the radio frequency-based WPSN to maximize the energy transfer efficiency. According to the numerical results, the proposed dynamic programming-based antenna resource allocation algorithm can achieve near-optimal energy transfer efficiency while reducing the computation complexity significantly, compared with the backtracking algorithm which always achieves the optimal allocation but usually not tractable in practical scenarios.**

***Index Terms*—Antenna resource allocation, dynamic programming, energy transfer efficiency, wireless powered sensor networks (WPSN), wireless power transfer (WPT).**

I. Introduction

Conventional wireless sensors [1], [2] are usually equipped with replaceable batteries, incurring additional maintenance cost in replacing batteries. Radio frequency (RF)-based wireless powered sensors provide a possible solution for solving such a dilemma [3]. However, the wireless charging rates in RF-based wireless powered sensors are usually unstable and low because of the time-varying characteristics of wireless channels and health concerns. To increase the energy transfer efficiency in wireless powered sensor networks (WPSN), using multiple energy transmitters and multi-antenna beamforming technology [4], [5] to simultaneously transfer energy to a specific wireless powered sensor have been proposed recently [6]–[10].

When multiple energy transmitters simultaneously transfer energy to a wireless device, the destructive interference among power beams may degrade the energy transfer efficiency [6]. To reduce the impact of the destructive interference on the energy transfer efficiency, the approach that classifies the power beams into groups based on the phase deviation has been proposed in several works [7]–[9]. However, the issues of distance diversity and the maximum phase deviation in a group were not investigated in the literature. In [10], the authors proposed the method that two power beams use different frequencies to reduce the destructive interference. However, all these aforementioned works did not consider the path loss and antenna resource allocation problems. Additionally, there exists a doubly near-far problem in the WPSN [11]. Thus, how to allocate the energy antenna resource to each wireless sensor for alleviating the doubly near-far problem and achieving fairness is also a challenging issue. To maximize the energy transfer efficiency, in this paper we aim to design a low-complexity antenna resource allocation algorithm for the WPSN which consists of multiple multi-antenna energy transmitters and multiple wireless powered sensors.

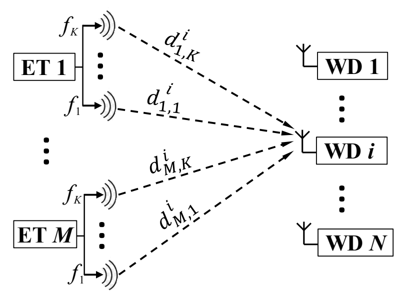


Fig. 1: System model.

The rest of this paper is organized as follows. Section II describes the system model and proposes a dynamic programming-based antenna resource allocation scheme. Section III conducts simulations to evaluate the performance of the proposed antenna resource allocation scheme. Finally, the concluding remarks are given in Section IV.

II. System Model and Proposed Antenna Resource Allocation Scheme

The considered system includes M energy transmitters (ET) and N wireless powered devices/sensors (WD). The energy transmitters use multi-antenna beamforming technology to support power transfer function. Each energy transmitter consists of K beamforming antennas which use the same frequency. The distance between WD n and the k-th antenna of ET m is denoted by $d^n_{m,k}$, as shown in Fig. 1.

According to the Friis transmission formula, the received power P_r at a wireless device attenuates with the distance d

between the wireless device and antenna which emits power P_t, i.e.,

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi d)^2}, \tag{1}$$

where G_t and G_r are the antenna gains of the transmitter and receiver, respectively, and λ is the wavelength of the radio signals.

Two energy beams received at WD n may have a phase deviation $\phi\in[-\pi,\pi]$ which can lead to constructive or destructive interference. The phase deviation ϕ is related to the distance difference $|d^n_{m_1,k_1} - d^n_{m_2,k_2}|$, i.e.,

$$\phi = \Big[\frac{2\pi|d^n_{m_1,k_1} - d^n_{m_2,k_2}|}{\lambda} \bmod 2\pi\Big] - \pi. \tag{2}$$

The effect of phase deviations on the energy transfer efficiency can be evaluated as follows. Assume that there are J_n antennas simultaneously transmitting energy to WD n. At WD n, the amplitude and phase of the received energy beam from antenna $a_{n,j}$ are $A^n_{a_{n,j}}$ and $\phi^n_{a_{n,j}}$, respectively. The index $a_{n,j} = (m,k)$ for some m and k depends on the antenna resource allocation. Then the aggregated signal $r_n(t)$ at WD n can be expressed by

$$r_n(t) = \sum_{j=1}^{J_n} A^n_{a_{n,j}} \cos(\omega t + \phi^n_{a_{n,j}}) = R_n \cos(\omega t + \theta), \tag{3}$$

where

$$R_n = \sqrt{\Big(\sum_{j=1}^{J_n} A^n_{a_{n,j}} \cos\phi^n_{a_{n,j}}\Big)^2 + \Big(\sum_{j=1}^{J_n} A^n_{a_{n,j}} \sin\phi^n_{a_{n,j}}\Big)^2}, \tag{4}$$

$$\theta = \tan^{-1}\Big(\frac{\sum_{j=1}^{J_n} A^n_{a_{n,j}} \sin\phi^n_{a_{n,j}}}{\sum_{j=1}^{J_n} A^n_{a_{n,j}} \cos\phi^n_{a_{n,j}}}\Big). \tag{5}$$

Thus, the average received power P^n_r at WD n is

$$P^n_r = \frac{1}{2}\Big[\Big(\sum_{j=1}^{J_n} A^n_{a_{n,j}} \cos\phi^n_{a_{n,j}}\Big)^2 + \Big(\sum_{j=1}^{J_n} A^n_{a_{n,j}} \sin\phi^n_{a_{n,j}}\Big)^2\Big]. \tag{6}$$

Based on (6), we define the energy transfer efficiency η of the system to be as follows.

$$\eta = \frac{\sum_{n=1}^{N} P^n_r}{P_t \sum_{n=1}^{N} J_n}, \tag{7}$$

where P_t is the transmit power of each antenna of energy transmitters.

The considered optimization problem is to find the optimal allocation $a^*_{n,j}$ to maximize the energy transfer efficiency η, subject to the constraint that every wireless device is allocated at least one antenna for energy transfer. To find the maximum η in (7), one can use the backtracking approach [12] based on the state space tree, where each node at level m of the state space tree indicates the possible allocation cases, i.e., not allocated ($n = 0$) or allocated to WD n ($n = 1, 2, \cdots, N$), of the antenna m ($m = 1, 2, \cdots, MK$). The backtracking-based algorithm based on the state space tree can be implemented using the recursive depth first search (DFS) algorithm, as shown in Algorithm 1. The complexity of the backtracking-based algorithm is bounded by $O((N+1)^{MK})$, which is highly complicated and intractable in practical scenarios.

Algorithm 1: Backtracking-Based Antenna Resource Allocation

procedure DFS(**node** v, **device** $\{1, \cdots, N\}$, **antenna** $\{m, \cdots, MK\}$)
  node u;
  visit v;
  compute η;
  if ($\eta \geq \eta_{max}$) **then**
    $\eta_{max} = \eta$;
    $optmal\_allocation = path(v)$; // the path from root to v
  end if
  for all children u of v **do**
    if promising(u) **then** // u satisfies the constraint
      DFS(u, $\{1, \cdots, N\}$, $\{m+1, \cdots, MK\}$);
    end if
  end for
end procedure

Algorithm 2: Dynamic Programming-Based Antenna Resource Allocation

// Allocate antennas to WD 1, denoted them by $A[1][1], \cdots, A[1][p[1]]$
DFS(v, $\{1\}$, $\{1, \cdots, MK\}$);
for all $2 \leq n \leq N$ **do** // Dynamic programming on index n
  for all WD $j < n$ **do**
    // Reallocate antennas $A[j][1], \cdots, A[j][p[j]]$ to WDs j and n
    DFS(v, $\{j, n\}$, $\{A[j][1], \cdots, A[j][p[j]]\}$); // Step 1
  end for
  Allocate free antennas to WD n if η increases; // Step 2
end for
Reallocate each allocated antenna to other WD if η increases; // Step 3
Release some allocated antennas if η increases; // Step 4
for all WD which has no antenna **do** // Step 5: satisfies the constraint
  Reallocate one allocated antenna to it. // which reduces η the least;
end for

To reduce the complexity of the antenna resource allocation problem, a dynamic programming-based algorithm is proposed in this paper, as shown in Algorithm 2. Initially, all antennas are possibly allocated to only WD 1 using the backtracking algorithm DFS(v, $\{1\}$, $\{1, \cdots, MK\}$). The resulting allocated antennas to WD 1 are denoted by $A[1][1], \cdots, A[1][p[1]]$, i.e., only $p[1]$ antennas are allocated to WD 1. Next, the dynamic programming approach is applied by increasing the index n in each iteration. In each iteration, there are 2 steps to be executed. For example, when $n = 2$, these antennas $A[1][1], \cdots, A[1][p[1]]$ are reallocated to WDs 1 and 2 using the backtracking algorithm DFS(v, $\{1, 2\}$, $\{A[1][1], \cdots, A[1][p[1]]\}$). In Step 2, each of those antennas not being allocated is allocated to WD 2 if the energy transfer efficiency η can be further increased. For subsequent iterations, the above two steps are executed repeatedly for all $n \leq N$. Instead, Step 1 reallocates antennas $A[j][1], \cdots, A[j][p[j]]$ to WDs j and n, where $A[j][1], \cdots, A[j][p[j]]$ are the antennas allocated to WD j in the previous iteration, and Step 2 allocates each of free antennas to WD n if η can be further increased, and so on. After completing all iterations on n, Steps 3 to 5 are executed. In Step 3, for each allocated antenna, if the η can be increased when it is reallocated to another WD, it must be reallocated. Subsequently, considering each allocated antenna, if the η can be further increased when it is released, its allocation is

TABLE I: Comparison of Computation Time (M= 5, K= 2).

N	Backtracking (s)	Dynamic Programming (s)
4	3.016	0.016
5	14.031	0.031
6	42.438	0.047
7	80.437	0.047
8	91.687	0.047
9	57.203	0.047
10	15.171	$<$0.001

TABLE II: Comparison of Computation Time (M= 4, K= 3).

N	Backtracking (s)	Dynamic Programming (s)
5	594.890	0.016
6	2903.234	0.031
7	9321.453	0.032
8	19688.700	0.047
9	27040.810	0.062
10	23209.440	0.063
11	11283.470	0.078
12	2382.453	$<$0.001

withdrawn in Step 4. Finally, Step 5 checks whether there exists any WD that has not been allocated any antenna. If yes, reallocate one allocated antenna, which reduces η the least, to it in order to satisfy the constraint that each WD must have at least one antenna for energy transfer. The complexity of Algorithm 2 reduces to $O(N \cdot 3^{MK})$, much less than that of Algorithm 1.

III. Numerical Results

In this section, we conduct numerical examples to evaluate the performance of the proposed antenna resource allocation algorithm. The positions of wireless devices are uniformly distributed over the area of 4×4 m^2, while the positions of energy transmitters are properly designed to be evenly located within the aforementioned area. The numbers of wireless devices and energy transmitters are N and M, respectively. Each energy transmitter has K beamforming antennas. In each energy transmitter, the beamforming antennas are separated by 2 cm. The radio frequency used for power transfer is assumed to be 915 MHz and the transmit power P_t of each beamforming antenna is 1 W. Both the antenna gains G_t and G_r at the transmitter and receiver, respectively, are set to 1. Additionally, the beamforming antennas can smartly use phase shifters to adjust the phases of power beams so that at each wireless device the phase deviations among power beams can be effectively eliminated [13]. Thus, in the numerical examples we assume that the phases of power beams at each wireless device are coherent, i.e., the phase deviation is zero.

The considered algorithms are executed in the same PC which has CPUs of 5.2 GHz i9-11900 processors and Win10 operating system. Table I and Table II compare the computation time of backtracking and dynamic programming-based algorithms under (M, K)=$(5, 2)$ and (M, K)=$(4, 3)$, respectively. The results show that the proposed dynamic programming-based algorithm reduces the computation complexity significantly. The allocation results for the cases (M, K, N) = (5, 2, 9) and (M, K, N) = (4, 3, 11) are shown in Figs. 2 and 3, respectively, where the red arrows indicate the antennas and the blue squares represent the wireless devices. The allocation results of the case (M, K, N) = (5, 2, 9) are the same for the backtracking and dynamic programming algorithms. However, for the case (M, K, N) = (4, 3, 11), the allocation result of dynamic programming algorithm is slightly different from that of the backtracking algorithm.

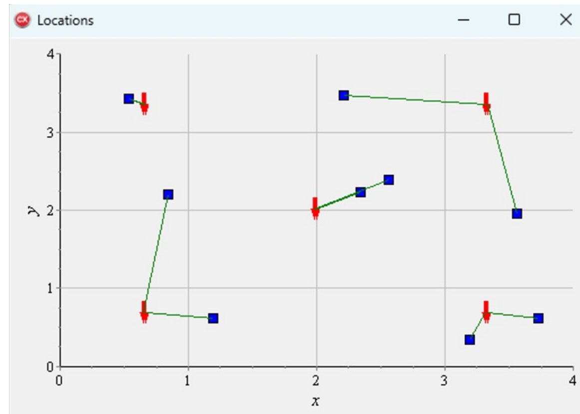
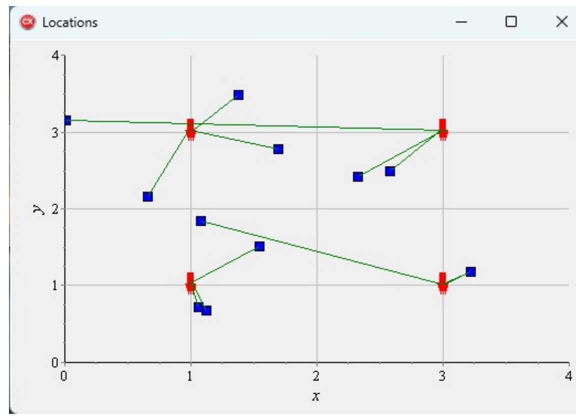
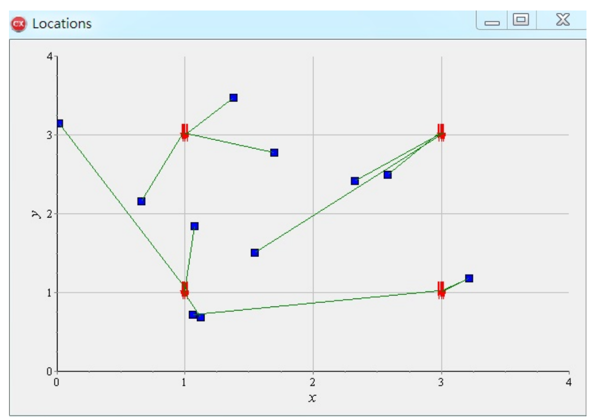


Fig. 2: Allocation results of M= 5, K= 2, and N= 9 for both the backtracking and dynamic programming algorithms.



(a) Backtracking



(b) Dynamic Programming

Fig. 3: Allocation results of M= 4, K= 3, and N= 11 for the backtracking and dynamic programming algorithms.

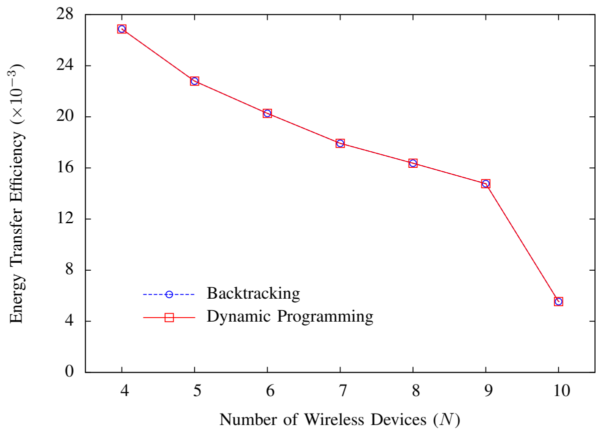


Fig. 4: Energy transfer efficiency versus the number N of wireless devices. (M= 5, K= 2)

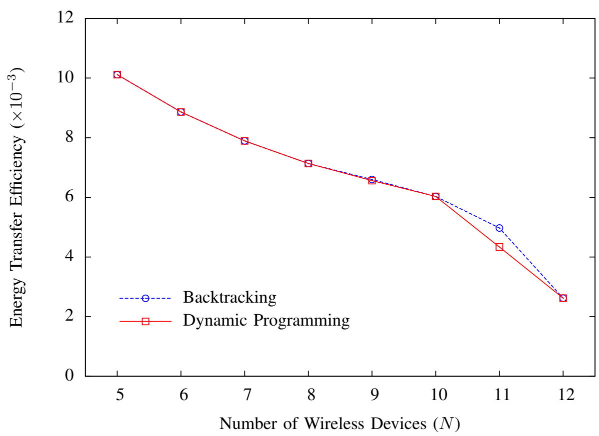


Fig. 5: Energy transfer efficiency versus the number N of wireless devices. (M= 4, K= 3)

The corresponding energy transfer efficiency of the cases in Table I and Table II are plotted in Figs. 4 and 5, respectively. Figures 4 and 5 show that the energy transfer efficiency of the proposed dynamic programming-based algorithm may be slightly lower than that of the backtracking-based algorithm which always achieves the optimal allocation. For example, in Fig. 5 the energy transfer efficiency of the proposed dynamic programming-based algorithm at $N = 11$ is less than that of the backtracking one. This is because the allocation results of the case $(M, K, N) = (4, 3, 11)$ for the proposed dynamic programming and backtracking algorithms are different, as shown in Fig. 3. However, the proposed dynamic programming-based algorithm makes the antenna resource allocation in the WPSN tractable and feasible from the aspect of computation time, as demonstrated in Tables I and II. Consequently, the proposed dynamic programming-based antenna resource allocation algorithm can achieve near-optimal energy transfer efficiency with acceptable computation complexity.

IV. Conclusion

In this work, we propose a dynamic programming-based algorithm to solve the antenna resource allocation problem of maximizing the energy transfer efficiency in the RF-based WPSN. The proposed dynamic programming-based algorithm can achieve near-optimal energy transfer efficiency while achieving relatively low computation complexity, compared with the backtracking algorithm which always obtains the optimal solution but with extremely high computation complexity. However, when the total number MK of antennas is larger than 15, the computation time of the proposed dynamic programming-based algorithm also grows rapidly and becomes unacceptable. Therefore, in the near future we intend to find a better algorithm which has much less computation complexity and achieves higher energy transfer efficiency. Additionally, the antenna resource allocation problem of maximizing the fairness or total harvesting energy and subject to other constraints such as satisfying the devices' charging rate requirement will be studied as well.

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