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Energy Beamforming Design with the Bat Algorithm for RF Wireless Power Transfer with Dynamic Metasurface Antennas

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ABSTRACT - This paper investigates the problem of energy beamforming for RF wireless power transfer (WPT) using dynamic metasurface antennas (DMAs). In contrast to previous approaches that employ approximations through alternate optimization methods, we propose a new method based on the Bat Algorithm (BA) to solve the optimization problem for beamforming in a more efficient manner. The proposed BA algorithm provides a robust and computationally efficient solution to the problem, considering the constraints of the system, including power transfer efficiency, antenna configurations, and DMA characteristics. Simulation results show that the BA-based approach achieves comparable or even superior performance in terms of power transfer efficiency and robustness under different scenarios. The proposed method offers a promising solution for future WPT systems with DMAs.

I. INTRODUCTION

In recent years, near-field (NF) wireless power transfer (WPT) has gained significant attention, particularly with the advent of metasurfaces and dynamic metasurface antennas (DMAs) capable of controlling electromagnetic waves at a granular level. DMAs enable precise energy beamforming, which is crucial for efficient power delivery in wireless communication systems. For instance, in multi-user extremely large-scale MIMO (XL-MIMO) systems the design of beam focusing patterns and optimal user grouping plays a key role in improving performance and energy efficiency [1].

Reconfigurable intelligent surfaces (RIS) further contribute to enhancing energy transfer in these scenarios by providing adaptive control of the channel environment, which is essential for mitigating path loss issues commonly encountered in NF conditions [2]. Moreover, advanced antenna designs, such as waveguide-fed metasurfaces, offer improved beamforming capabilities by leveraging their structural properties to optimize the distribution of electromagnetic waves [3]. These technological advancements allow more efficient energy delivery, especially in applications involving dynamic reconfigurations and multi-user settings.

In the context of WPT, DMAs stand out for their ability to dynamically reconfigure the transmission to the environment, allowing for targeted energy delivery in complex multi-user setups. The flexible nature of these antennas enables adaptive phase and amplitude adjustments that are crucial for maintaining consistent energy transfer efficiency despite changing spatial distributions of users' locations. DMAs can maintain focused beams in NF conditions while minimizing interference with adjacent users [4]. As such, DMAs have become integral to improving energy efficiency and reliability in various WPT scenarios, particularly in environments where WPT must adapt in real-time to user movement and distribution.

One promising approach to maximize energy efficiency in WPT systems using DMAs for energy beamforming is given by [4]. The authors carefully adjust the phase and amplitude of the reflected signals, aiming to focus the energy on specific locations by means of the DMA, significantly improving the WPT rate. Yet, maximizing the energy efficiency in such a context yields a mathematically complex optimization problem. In [4], with the objective of minimizing the power loss while maximizing coverage, an alternate optimization problem is proposed, which iteratively approximates the optimal solution. However, problems solved by alternate optimization are usually non-convex, while the computational complexity becomes a burden due to the large number of involved variables. In this context, heuristic algorithms, such as the bat algorithm (BA), have emerged as alternative approaches with lower complexity [5].

In this paper, we propose an energy beamforming technique based on the BA for WPT using DMA technology. The BA, inspired by the echolocation behavior of bats, is particularly suited for global optimization tasks in engineering due to its ability to explore and exploit the search space effectively. Its ability to solve convex optimization problems in DMA-based WPT systems has demonstrated rapid convergence and concentrated energy distribution patterns. Our numerical results show that significant improvements in NF power transfer efficiency can be achieved. This was illustrated by employing the BA in two distinct scenarios operating at a frequency of 5 GHz.

II. PROBLEM FORMULATION

We assume a WPT system aiming to deliver power to K single-antenna energy-harvesting (EH) devices. We consider a DMA working as a transmitter fixed on the ceiling of a room, while the devices are distributed in three-dimensional space. We define the location of the k-th device as a vector $\mathbf{p}_k = [x_k, y_k, z_k]$, where $k = 1, 2, \ldots, K$.

To ensure the NF propagation condition, a user k located at position $\mathbf{p}_k$, at a distance d_k from the transmitter, must satisfy $d_{\mathrm{fs}} < d_k < d_{\mathrm{fr}}$. Here, $d_{\mathrm{fs}} = \sqrt[3]{\frac{D^4}{8\lambda}}$ defines the Fresnel distance, and $d_{\mathrm{fr}} = \frac{2D^2}{\lambda}$ defines the Fraunhofer distance, where λ is the wavelength and $D = \sqrt{2}L$ is the antenna's effective diameter, with L being the antenna length. It is important to remark that devices positioned within this range will experience NF effects, where the curvature of the electromagnetic wavefront and the non-uniform phase distribution play a significant role in shaping the signal propagation characteristics.

The DMA model employed in this work is based on [4], which is composed of N_v RF chains, each connected to a waveguide with N_h metamaterial elements. Thus, the total number of elements is $N = N_v \times N_h$. Also, $M = \min(N_v, K)$ energy symbols are the inputs of a digital beamforming, which controls the DMA.

The transmitted power is defined by

$$P^{\mathrm{TX}} = \sum_{m=1}^{M} |\mathbf{HQW}_m|^2, \tag{1}$$

and the power received by the k-th device is

$$P_k^{\mathrm{RX}} = \sum_{m=1}^{M} |\mathscr{C}_k^H \mathbf{HQW}_m|^2, \tag{2}$$

where $\mathscr{C}_k$ represents the channel gain vector between the transmitter and the k-th EH device, $\mathbf{H} \in \mathbb{C}^{N \times N}$ is the microstrip propagation diagonal matrix, as described in [4], $\mathbf{Q} \in \mathbb{C}^{N \times N}$ contains the configurable weights of the metamaterial elements, and $\mathbf{W}_m$ is the precoding vector corresponding to the m-th energy symbol.

Then, the problem lies in minimizing P^{TX} while ensuring a minimum received power $P_k^{\mathrm{RX}} \geq \delta$ for each device. The optimization problem can be written as

$$\textbf{P1:} \quad \underset{\mathbf{Q}, \mathbf{W}_m}{\text{minimize}} \quad P^{\mathrm{TX}} = \sum_{m=1}^{M} |\mathbf{HQW}_m|^2 \tag{3a}$$

$$\text{subject to} \quad P_k^{\mathrm{RX}} = \sum_{m=1}^{M} |\mathscr{C}_k^H \mathbf{HQW}_m|^2 \geq \delta, \tag{3b}$$

$$\mathbf{Q}, \mathbf{W}_m \in \mathscr{L}, \tag{3c}$$

where the symbol $\mathscr{L}$ denotes the Lorentzian interval in the complex plane, according to [4].

Finding the matrices $\mathbf{Q}$ and $\mathbf{W}_m$ form a convex problem given the quadratic structure in the received power expression, which depends on the interaction between $\mathbf{Q}$ and $\mathbf{W}_m$. To solve this optimization problem, various methods can be employed, such as convex programming, the method of Lagrange multipliers, the gradient algorithm [6], alternate optimization [4] or, alternatively, heuristic approaches [5]. A modern and promising approach is the BA, which is inspired by the echolocation behavior of bats. BA is effective in handling complex, high-dimensional problems due to its ability to balance exploration and exploitation within the solution space. Compared to other heuristic methods, such as the genetic algorithm or particle swarm optimization, BA has demonstrated better performance in finding high-quality solutions in fewer iterations, making it an attractive choice for optimizing systems with DMAs.

III. PROPOSED BAT ALGORITHM

The BA, developed by Yang [5], is inspired by the echolocation behavior of bats, who use echolocation, emitting sound pulses and analyzing the returning echoes to detect prey, obstacles, and other environmental features in dark settings. The echolocation principle leverages differences in time and frequency shifts between pulse emission and echo reception. The BA can be formulated using the following fundamental rules [6]:

1. All bats emit sound pulses to estimate distances to prey or obstacles.
2. Each bat flies randomly but can also adjust its movement based on current optimal positions.
3. The properties of the sound pulses (frequency, loudness, and pulse emission rate) vary during the search process to fine-tune their exploration and exploitation balance.

For the implementation, the movement of the bats is discretized over time and updated after each iteration t, assuming the colony is composed of n bats. Each bat in the colony is assigned an index i and represents a potential solution to the optimization problem **P1**. In this work, the i-th bat in the t-th iteration is mathematically described by a matrix combining $\mathbf{Q}$ and $\mathbf{W}_m$, *i.e.*, containing the configurable weights of the metamaterial elements and the precoding vectors. Then, each bat i of the colony is initialized with a three-dimensional position $\mathbf{X}_i$, velocity $\mathbf{V}_i$, frequency $\mathbf{F}_i$, loudness A_i, and pulse rate r_i. At each time step t, the positions and velocities are updated.

The frequency of each bat is updated within a predefined range

$$\mathbf{F}_i = \mathbf{F}_{\min} + (\mathbf{F}_{\max} - \mathbf{F}_{\min}) \circ \beta, \tag{4}$$

where $\mathbf{F}$min and $\mathbf{F}$max are matrices representing the minimum and maximum frequencies, respectively, β is a matrix composed of uniformly distributed random values in $[0, 1]$, while $\circ$ is the Hadamard product. Here, all matrices match the size of the position matrix $\mathbf{X}_i$.

Based on $\mathbf{F}_i$, the velocity $\mathbf{V}_i^{t+1}$ is calculated as

$$\mathbf{V}_i^{t+1} = \mathbf{V}_i^t + \left(\mathbf{X}_i^t - \mathbf{X}_{\mathrm{best}}\right) \circ \mathbf{F}_i, \tag{5}$$

where $\mathbf{X}_{\text{best}}$ is the current global best solution.

The new position of the bat, denoted as $\mathbf{X}_i^{t+1}$, is computed based on the flying strategy. If the bat is in *global search* flight mode, the new position is calculated by

$$\mathbf{X}_i^{t+1} = \mathbf{X}_i^t + \mathbf{V}_i^{t+1}, \tag{6}$$

while in *local search* flight mode, the new position can be estimated by choosing the best case among the position calculated using (6) and

$$\mathbf{X}_i^{t+1} = \mathbf{X}_{\text{best}} + \Omega A^t, \tag{7}$$

where Ω is a matrix with elements in the range $[-1,1]$ generated randomly with normal distribution and A^t is a scalar containing the average pulse amplitudes.

The flying mode of the i-th bat is chosen depending on the pulse emission rate r_i, which can be calibrated by the parameter $\gamma \in [0,1]$ according to

$$r_i^{t+1} = r_i^{\max}[1 - e^{-\gamma t}], \tag{8}$$

where $r_i^{\max}$ is the maximum attainable pulse emission rate. If a solution is better, then the new position is accepted, and the loudness and pulse emission rate are updated. The loudness is updated by

$$A_i^{t+1} = \alpha A_i^t, \tag{9}$$

where α is a constant smaller than one. Thus, at each iteration A_i^{t+1} is reduced with respect to A_i^t.

Finally, new solutions are accepted only if P^{TX} is minimized. Algorithm 1 summarizes the overall BA-based optimization solution for the DMA-assisted RF-WPT system.

Algorithm 1 BA-Based Optimization Algorithm

Input: n, K, $\mathbf{p}_k$, δ, $\mathbf{F}_{\max}$, $\mathbf{F}_{\min}$
Initialize:
$r_i = 0$, $A_i = 1$ for each bat
Initialize population of bats for $i = 1,\ldots,n$
Evaluate the objective function (3a) for each bat positions $\mathbf{X}_i$, ensuring constraint (3b)
Set the global best position $\mathbf{X}_{\text{best}}$ and $P_{\text{best}}^{\text{TX}}$
while stopping criterion not met **do**
  for each bat $i = 1,\ldots,n$ **do**
    Calculate $\mathbf{F}_i$ using (4)
    Calculate $\mathbf{V}_i^{t+1}$ using (5)
    Calculate $\mathbf{X}_i^{t+1}$ using (6)
    if rand $> r_i$ **then**
      Calculate $\mathbf{X}_i^{t+1}$ using (7)
    end if
    Evaluate $P_{\text{new}}^{\text{TX}}$, P_k^{RX}
    if $P_{\text{new}}^{\text{TX}} < P^{\text{TX}}$, and $P_k^{\text{RX}} \geq \delta$ **then**
      Accept the new solution $\mathbf{X}_i^{t+1}$
      Update r_i^{t+1} and A_i^{t+1} using (8)-(9)
      if $P_{\text{new}}^{\text{TX}} < P_{\text{best}}^{\text{TX}}$ **then**
        Update $P_{\text{best}}^{\text{TX}}$
      end if
    end if
  end for
end while
Output: $P_{\text{best}}^{\text{TX}}$, $\mathbf{X}_{\text{best}}$

IV. SCENARIOS

To thoroughly evaluate the system's performance, two scenarios are tested, each designed to simulate different real-world conditions of WPT:

- **Scenario 1**: A single device ($K = 1$) is receiving wireless power, an isolated charging scenario.
- **Scenario 2**: Two devices ($K = 2$) are receiving wireless power simultaneously, testing the system's ability to handle multiple users effectively.

In each scenario, the matrices $\mathbf{Q}$ and $\mathbf{W}_m$ are optimized using the BA to ensure that the energy is focused on the intended devices while considering system constraints.

V. RESULTS

Considering Scenarios 1 and 2, the simulations utilized a frequency of 5 GHz with an antenna length of $L = 0.2$, resulting in $d_{\text{fs}} = 2.67$ m and $d_{\text{fr}} = 7.79$ m. The DMA was fixed on the ceiling, located at the center of a flat region measuring 10×10 meters, at a height of 3 meters at position $[5,5,3]$. Then, to ensure NF operation, the users were placed at positions $\mathbf{p}_1 = [3,7,0]$ and $\mathbf{p}_2 = [8,3,0]$. The received power threshold is $\delta = 10\ \mu\text{W} = -10$ dBm.

For the BA, the initial iteration is set to $t = 0$, and the maximum number of iterations is 1000. The initial volume of the pulses is set to $A_0 = 1$, and the initial pulse emission rate is $r_0 = 1$. The algorithm includes the parameters $\alpha = 0.5$ and $\gamma = 0.9$ to control the search dynamics. The number of bats is set to $n = 500$.

In this BA configuration, the search space assumes the interval of the Lorentzian distribution, providing a structured exploration across amplitude and phase intervals. Specifically, the amplitude search interval is set from -0.5 to 0.5, and the phase search interval spans from 0 to 1. The amplitude and phase are coupled in this configuration, meaning that variations in amplitude directly influence phase adjustments and vice versa. This coupling is designed to accommodate the characteristics of Lorentzian dynamics, allowing the algorithm to effectively explore variations in both amplitude and phase simultaneously within the specified range, ensuring that the optimization process remains synchronized and converges toward optimal solutions.

Fig. 1 illustrates the obtained transmitted power as a function of the iterations of the proposed BA approach for Scenarios 1 and 2. As we observe, the algorithm required around 25 iterations to optimize both scenarios, becoming stable beyond that point. For Scenario 1, after 25 iterations, the transmit power is of $P^{\text{TX}} = 30.37$ dBm, while $P^{\text{TX}} = 36.22$ dBm for Scenario 2. It is also important to mention that the proposed BA approach was able to maintain the threshold power of $\delta = 10\ \mu$W in both scenarios. In Scenario 1, a lower transmission power

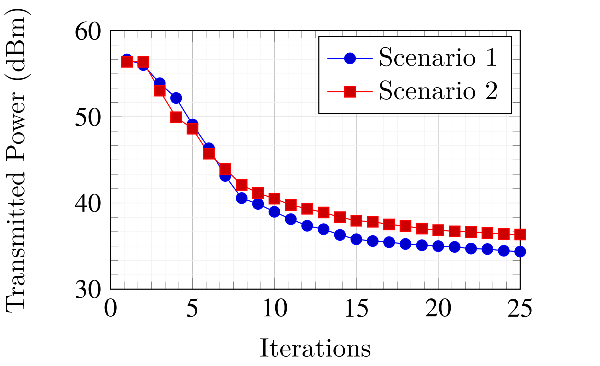

Fig. 1: *Transmitted power vs. the number of iterations for Scenarios 1 and 2.*

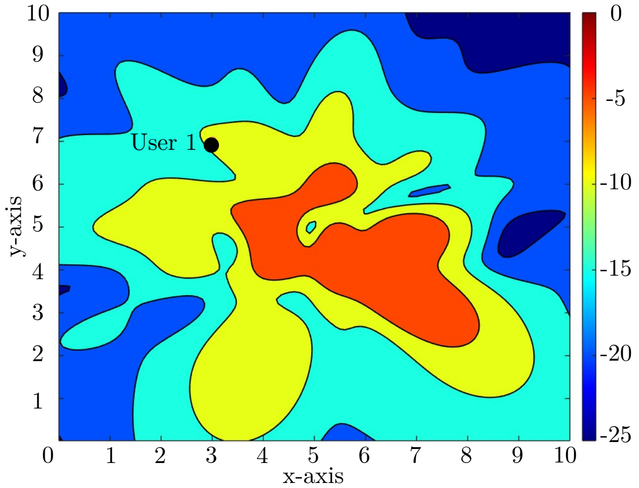

Fig. 2: *Received power in the x-y plane at the user's location for Scenario 1, in dBm.*

was achieved compared to Scenario 2. This outcome aligns with expectations, as providing power to more than one user requires additional energy. These results are promising and highlight the BA as an effective solver for this problem. This conclusion becomes evident when comparing the results obtained here to those presented in [4], where the P^{TX} for the operating frequency of 5 GHz was approximately 37.5 and 39 dBm for $K = 1$ and $K = 2$, respectively, which is higher than the results obtained in this work.

Fig. 2 and Fig. 3 illustrate the received power in the x-y plane where the users are located, respectively for Scenarios 1 and 2. As we can observe by the color gradient in both figures, the users are located in a region where the power is above $\delta = -10$ dBm, which serves as a problem-solving criterion. Thus, the proposed BA optimization approach is a viable solution for energy beamforming with DMS, being able to charge multiple devices and also minimizing P^{TX} compared to [4].

VI. CONCLUSIONS

This paper presented an innovative approach to energy beamforming in RF WPT using DMAs by implementing a BA-based optimization approach. BA offers a robust and computationally efficient solution, converging after a few iterations, while effectively handling the complexity and high dimensionality inherent in DMA configurations. Simulation results demonstrate that the BA-based approach minimizes the power consumption compared to recent approaches in the literature, showing robustness across various WPT scenarios.

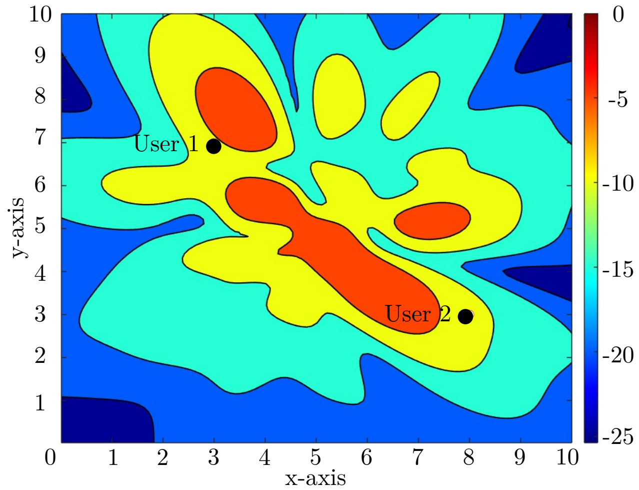

Fig. 3: *Received power in the x-y plane at the users' location for Scenario 2, in dBm.*

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