Multi-Objective Learning Methods for Wireless-Powered Communication Network

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ABSTRACT

This paper characterizes rate region of wireless powered communication networks (WPCNs) using deep neural networks (DNNs). In the multi-user WPCN, each user first harvests energy of radio-frequency (RF) signals radiated from a hybrid access point (H-AP) in a downlink phase. Then, the users utilize their energy to send data to the H-AP based on dynamic time-division-multiple-access (TDMA) protocol. A DNN is introduced to optimize time allocation solutions of the WPCN which achieve the Pareto-optimal boundary points of the rate region. Unlike conventional optimization algorithms which require multiple executions for each boundary point, the proposed DNN method universally identifies the entire Pareto front only with a single inference computation of the trained DNN.

I. INTRODUCTION

In recent times, wireless powered communication networks (WPCNs) have witnessed a great research interest due to cost-effective and energy-efficient implementation of energy-constrained devices. Throughput maximization problems of the WPCN systems were optimally tackled via convex optimization techniques [1]. Due to the subsequent downlink and uplink phases, the WPCN suffers from the "doubly near-far" effect. To mitigate this, the common-throughput maximization task was investigated in [1] to guarantee the rate fairness of multiple users. However, this approach forces all the users to achieve the identical data rate performance regardless of their quality-of-service requirement.

A fundamental approach to handle this issue is to characterize complete tradeoff curves of achievable data rate, i.e., the Pareto boundary of the rate region. To this end, it is essential to tackle multi-objective optimization tasks. One possible approach is to alternatively solve the weighted sum throughput maximization problem, whose optimal solution has been provided in [1]. However, this algorithm can only identify a sole Pareto optimal solution at each execution, thereby requiring several repetitions for obtaining the entire tradeoff boundary.

This paper proposes a new deep learning framework [2] that characterizes the rate region of the WPCN systems instantly. To this end, a deep neural network (DNN) is designed to accept weights as side information. As a result, the trained DNN can generate multiple Pareto optima simultaneously. Numerical results validate the effectiveness of the proposed framework.

II. SYSTEM MODEL

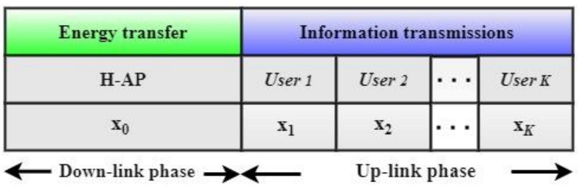

Fig. 1. Frame structure of WPCN.

We consider the WPCN systems [1] where a hybrid access point (H-AP) charges K users by conveying energy-bearing radio-frequency (RF) signals in the downlink (DL) phase. In the subsequent uplink (UL) phase, the users transmit their data symbols back to the H-AP using wirelessly harvested energy. As shown in Fig. 1, a dynamic time division multiple access (TDMA) approach is adopted to facilitate multi-user detection at the H-AP.

Let h_i and g_i be the DL and the UL channel gains between H-AP and user i, respectively. Assuming the channel reciprocity, both the DL and UL channel power gains are modeled as$h_i = g_i = 10^{-3}\rho_i^2 D_i^2$, were ρ_i^2 is the exponential random variable with unit mean and D_i denotes the distance between H-AP and user i. Then, the achievable data rate of user i is written by

$$f_i(\mathbf{a},\mathbf{x}) = x_i \log_2\left(1 + a_i \frac{x_0}{x_i}\right) \quad (1)$$

where x_0 accounts for the time assigned for the DL phase, x_i is the UL time duration allocated to user i, and $\mathbf{x} = [x_0,\ x_1, \dots\ x_K]$. Here, a_i represents the effective channel gain of user i given by

$$a_i = \frac{\zeta h_i g_i P_A}{\Gamma\sigma^2}, \qquad i = 1, \dots, K \quad (2)$$

where ζ is energy harvesting efficiency at each receiver, P_A is transmit power budget at the H-AP and Γ represents the signal-to-noise ratio (SNR) gap from the additive white Gaussian noise channel capacity.

III. MULTI-OBJECTIVE WPCN OPTIMIZATION

This section formalizes the multi-objective WPCN optimization task. We define a vector-valued rate function $\mathbf{f}\,(\mathbf{a},\mathbf{x}) \triangleq [f_1(\mathbf{a},\mathbf{x}),\ f_2(\mathbf{a},\mathbf{x}), \dots, f_N(\mathbf{a},\mathbf{x})]$. Then, the rate region characterization problem can be formulated as a multi-objective optimization task expressed by [3], [4].

$$\text{(P1)}:\ \max_{x}\quad \mathbf{f}(\mathbf{a},\mathbf{x}).$$
$$\text{subject to:}\ \sum_{i=0}^{N} x_i = 1\,,\ \ i = 1, \dots, N. \quad (3)$$

Optimal solutions to (P1) are known as Pareto solutions [4]. A Pareto optimal solution is the uppermost boundary point of a tradeoff curve at the outermost right edge. The problem can be solved by scalarizing (P1) with a weighted-sum-objective [4]. Let $\mathbf{w} = [w_1,\ w_1, \dots, w_N]^T$, is a weight vector whose element $w_i \geq 0$ indicates the *i*-th objective function $f_i(\mathbf{a},\mathbf{x})$ contribution. To preserve generality, we assume that $\sum_{i=1}^{N} w_i = 1$ without sacrificing any generality. Then, the weighted-sum-objective maximization task is given by

$$\text{(P2)}:\ \max_{x}\ \ \mathbf{w}^{\mathrm{T}}\mathbf{f}(\mathbf{a},\mathbf{x}) = \sum_{i=1}^{n} w_i f_i(\mathbf{a},\mathbf{x}).$$
$$\text{subject to:}\ \sum_{i=0}^{N} x_i = 1\,,\ \ i = 1, \dots, N. \quad (4)$$

It is to be noted that (4) can be solved traditionally by obtaining a sole Pareto optimal solution that is dedicated to $\mathbf{w}$. For each $\mathbf{w}$, let $g_w: \mathbb{R}^A \longrightarrow \mathbb{R}^X$ be an arbitrary optimizer for (P2). The solution $\mathbf{x}$ can then readily be obtained as

$$\mathbf{x} = g_{\mathbf{w}}(\mathbf{a}). \quad (5)$$

Utilizing (5) into (P2), the functional optimization task can be formulated as

$$\text{(P3)}: \max_{g_{\mathbf{w}}(\cdot)} \sum_{i=1}^{n} w_i f_i\big(\mathbf{a}, g_{\mathbf{w}}(\mathbf{x})\big).$$

$$\text{subject to: } \sum_{i=0}^{N} x_i = 1\,, \quad i = 1, \dots, N. \qquad (6)$$

It is worth mentioning that the complete characterization of the Pareto optimal tradeoff can be obtained by executing the optimization algorithm $g_{\mathbf{w}}(\cdot)$ for all possible weight realization $\mathbf{w}$, which requires prohibitive computation complexity.

The propose method identifies multiple Pareto optimal solutions simultaneously with a single run of a generic optimizer $g(\cdot)$, which accepts the weights $\mathbf{w}$ as side information. As a result, (5) is modified as

$$\mathbf{x} = g(\mathbf{a}, \mathbf{w}). \qquad (7)$$

Considering universal optimizer, a multiple Pareto optimal problem, a universal formalism of (P2) for all possible $\mathbf{w} \in \mathcal{W}$ can be represented as

$$\text{(P4)}: \max_{g(\cdot)} \mathbb{E}_{\mathcal{W}}\left[\sum_{i=1}^{N} w_i f_i\big(\mathbf{a}, g(\mathbf{a}, \mathbf{w})\big)\right]. \qquad (8)$$

As shown in Fig. 2, we exploit a deep neural network (DNN) to model the computation strategy in (7) as

$$\mathbf{x} = g_\theta(\mathbf{a}, \mathbf{w}), \qquad (9)$$

where θ indicates a set of trainable parameters. The training problem can then be formalized as

$$\text{(P5)}: \max_{\theta} \mathcal{J}(\theta) \triangleq \mathbb{E}_{\mathbf{a},\mathcal{W}}\left[\sum_{i=1}^{N} w_i f_i\big(\mathbf{a}, g_\theta(\mathbf{a}, \mathbf{w})\big)\right]. \qquad (10)$$

The above problem can be readily solved by existing gradient-based training algorithms, e.g., the Adam optimizer.

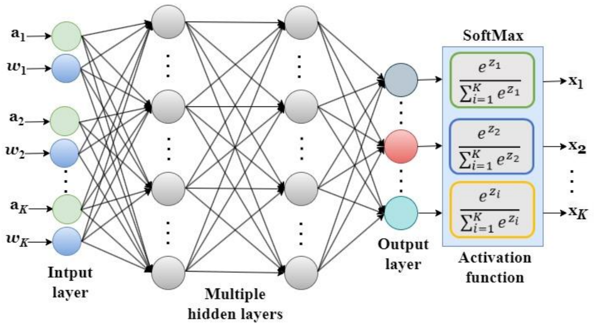

Fig. 2. Proposed DNN architecture.

IV. RESULTS AND DISCUSSIONS

For simulations, a three-layer fully-connected DNN is employed with 100 hidden neurons. The ReLU is used as hidden activations, whereas the softmax function is adopted at the output layer to guarantee the unit-sum constraint (3). The Adam optimizer is used as the training algorithm, with a learning rate of 0.003, a batch size of 2000, and 1000 validation samples. Also, the noise power spectral density is set to -160 dBm/Hz and bandwidth is set as 1MHz. The energy harvesting efficiency for is fixed as $\zeta = 0.5$, and the SNR gap is given as $\Gamma = 9.8$ dB.

Fig. 3 provides the rate region identified by the proposed DNN approach for $P_A = 20$ and 30 dBm. For comparison, we also plot the performance of the global optimal algorithm [1] dedicated to the weighted sum throughput maximization problem. The proposed framework achieves almost identical rate region generated by the global optimal algorithm. This implies that the proposed framework offers sufficient university of the boundary points with a sole inference computation of the trained DNN.

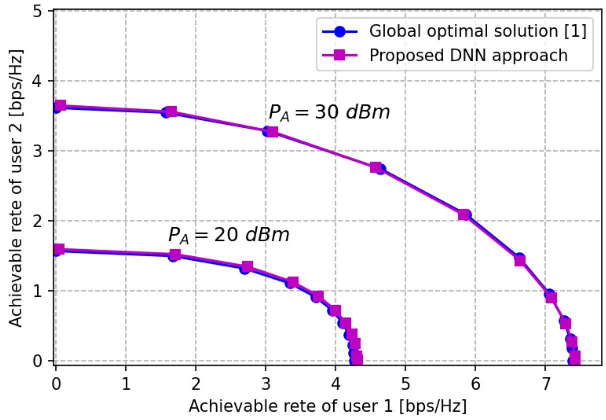

Fig. 3. Optimized rate region of two-user WPCN systems.

V. CONCLUSION:

This paper has proposed a novel deep-learning approach to characterize the rate region of the WPCNs. To this end, we have formulated a multi-objective optimization task that identifies the Pareto optima of the achievable rate region. This problem has been tackled by the scalarization technique which maximizes the weighted sum objective. To find multiple Pareto optimal simultaneously, the weights are employed as side infor mation of a generic multi-objective optimizer function. This is modeled by a DNN which is trained over a number of samples of channels and weights. Numerical results have demonstrated the universality of the proposed DNN method for characterizing multiple Pareto-optimal solutions at the same time.

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