Joint Optimization of Spectral Efficiency and Energy Harvesting in D2D Networks Using Deep Neural Network

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***Abstract*—In this work, we study the joint optimization of energy harvesting and spectrum efficiency in wireless device-to-device (D2D) networks where multiple D2D pairs adopt simultaneous wireless information and power transfer (SWIPT) functionality with a power-splitting policy. To observe the trade-off relationship between spectrum efficiency and energy harvesting via SWIPT, we construct an objective function using the weighted sum method, which scalarizes the dominant with spectrum efficiency and energy harvesting, and attempt to find the optimal transmit power and power-splitting ratio to maximize the objective function. Typical iterative search algorithms such as exhaustive search (ES) or gradient search (GS) with a log barrier function are employed to find the global optimum and sub-optimum, respectively. Furthermore, we apply a deep neural network (DNN) learning algorithm to deal with the non-convexity of the objective function with an effective loss function. The simulation results verify the trade-off relationship between spectrum efficiency and energy harvesting, and show that the DNN-based algorithm can achieve a near-global optimal solution with computational complexity much lower than that of the optimization-based iterative algorithms.**

***Index Terms*—Deep neural network, spectrum efficiency, energy harvesting, power-splitting, optimization.**

I. Introduction

The exponentially increasing demands for high data rate and energy-efficient use of transmit power in communication networks have triggered an urgent need to efficiently utilize the limited radio bandwidth to improve spectrum efficiency. To cope with this challenge, device-to-device (D2D) communication has been proposed, which enables direct transmission between proximate devices without relaying information through the base station, thereby improving spectral efficiency and system capacity [1]. As the device's functions become more complex and the information that needs to be processed increases, the power shortage problem of a D2D node is emerging [2]. To enhance the energy efficiency of mobile devices, wireless energy harvesting that gathers ambient energy from external sources for wireless autonomous devices has garnered considerable attention recently [3]. Simultaneous wireless information and power transfer (SWIPT) is a wireless energy harvesting technique that exploits both information and power simultaneously, exploiting the interference power from ambient energy sources and yielding higher information transmission efficiency. Therefore, the importance of SWIPT is emphasized in D2D networks, which takes into account of energy harvesting as well as information exchange.

There have been many studies on the wireless power transfer. The authors of [4] proposed two types of receiver architectures, separated versus integrated information and energy receivers. The rate-energy trade-off for the two architectures are characterized by a rate-energy region and the optimal transmission strategy is derived to achieve different rate-energy trade-offs. In [5], the authors showed fundamental trade-offs in designing wireless Multiple-Input Multiple-Output (MIMO) systems; an outer bound for the achievable rate-energy region. In [6], random and prioritized access policies were proposed to improve the throughput of up/down links and energy harvesting in cognitive D2D communication. In [7], an energy-efficient stable matching approach for joint power control was proposed to solve the resource allocation problem, which optimized the energy efficiency performance and energy harvesting in energy-harvesting-based D2D communication. In [8], the authors used stochastic geometry to protect the available spectrum for a limited number of D2D transmissions and increase the amount of time during which D2D users could harvest energy.

On the other hand, the increased diversity and complexity of mobile network architectures has made it impossible to control a number of network elements. Therefore, embedding multi-purpose machine intelligence in future mobile networks attracts unrivaled research attention [9], [10]. Deep learning is a sub-branch of machine-learning, which essentially enables an algorithm to make predictions, classifications, or decisions based on data, without being explicitly programmed. A key advantage of deep learning is that it can automatically extract high-level features from data that has complex structure and inner correlations. Deep neural network (DNN) is a kind of deep learning which can solve the optimization problem, and it has been widely applied these days. DNN can solve complex nonlinear problems via a simple back-propagation algorithm without employing complicated mathematical models [11], they have been considered as emerging candidates to resolve the complex resource management problems in wireless networks.

With these advantages of deep learning mentioned above, studies for applying deep-learning technology have been conducted to solve various problems in wireless networks. In [12]–[14], DNN-based power controls were proposed to maximize spectral efficiency or energy efficiency in interference channels. In the power control problem, a DNN was used as a functional approximate to evaluate the performance of the weighted minimum mean square error algorithm. In [15], the author proposed a DNN design for maximizing the spectral efficiencies of secondary users while reducing the interference to the primary users in cognitive radio networks. In [16], the author proposed deep learning-based namely deep belief network (DBN) to approximate the optimal solution in a SWIPT-enable multi-carrier non-orthogonal multiple access (MC-NOMA) system with TS-based receivers, which minimizes the total transmit power of the system for satisfying QoS of each user equipment in terms of data-rate and energy harvesting. The authors of [17] proposed dual mode SWIPT with deep long short-term memory (LSTM) recurrent neural network (RNN) based adaptive mode switching (MS) algorithm to maximize the achievable rate under the energy-causality constraint by adjusting the MS threshold in point-to-point SWIPT system.

In this work, we investigate the joint optimization of spectral efficiency and energy harvesting in a SWIPT-based D2D network with

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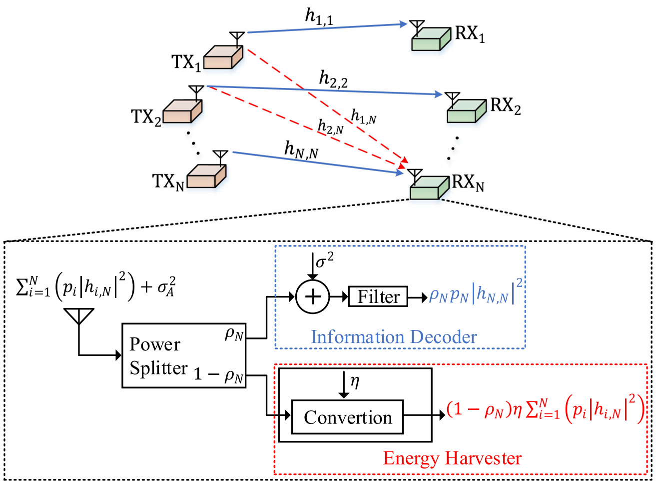


Fig. 1. System model.

power-splitting policy. For this purpose, we build the objective function as a function of the transmit power and power splitting ratio for D2D pairs, as a tool to quantitatively express the trade-off relationship between spectral efficiency and energy harvesting. We first use optimization-based iterative methods, such as exhaustive search (ES) and gradient search (GS) with barrier, to obtain the solutions for the transmit power and power splitting ratio for D2D pairs. More importantly, we suggest a DNN-based algorithm operating in an unsupervised manner, and compare its results with those of the optimization-based iterative methods, in terms of the sub-optimality and time complexity. To the best of our knowledge, this is the first attempt to investigate the trade-off relationship between spectral efficiency and energy harvesting in a SWIPT-based D2D network. Furthermore, the DNN design proposed in this work is based on unsupervised learning, which does not require any solution label and can therefore decrease the time complexity while providing near-global optimality as compared to other iteration-based sub-optimal algorithms.

II. System Model and Problem Statement

We consider a wireless-power-transfer D2D network consisting of N transmitter and receiver pairs. The channel between a transmitter and receiver is denoted as $h_{i,j}$, and it is assumed to follow a discrete-time block fading model where the channel state remains constant over a transmission block as in [18] and [19]. Furthermore, the channel gain, $|h_{i,j}|^2$, is assumed to be an independent and identically distributed (i.i.d.) Rician random variable with mean $\mu_{i,j}$, because line-of-sight (LOS) propagation is appropriate for energy harvesting [18]. The D2D receiver i adopts a power-splitting policy that divides the power into two portions by controlling the power-splitting ratio (ρ) for providing SWIPT functionality with conversion rate η [19], as shown in Fig. 1. That is, the power-splitting ratio ρ_i for the D2D receiver i splits the received power into information power and energy harvesting power, where $0 \leq \rho_i \leq 1$ for $1 \leq i \leq N$. In addition, there are two types of noise, namely antenna noise (n_A) and base-band noise (BBN) (n) at the wireless-power receivers [18]. We assume that n_A and n follow a complex Gaussian distribution, such that $n_A \sim \mathcal{CN}(0, \sigma_A^2)$ and $n \sim \mathcal{CN}(0, \sigma^2)$. In this network, the co-channel interference caused by sharing the same spectrum among all the D2D pairs degrades spectral efficiency, but increases harvested energy. It is noted that the D2D receivers cannot harvest energy from n_A and n, because the noise powers are relatively small when compared to the data and interference signals [18]–[20].

Let p_i, γ_i, and r_i be the transmit power, signal-to-interference-plus-noise ratio (SINR), and the spectral efficiency of the D2D pair i, respectively. Then, the achievable spectral efficiency of the D2D network can be expressed as

$$R(\vec{p},\vec{\rho}) = \sum_{i=1}^{N} r_i(\vec{p},\vec{\rho}) = \sum_{i=1}^{N} \log_2(1+\gamma_i)$$
$$= \sum_{i=1}^{N} \log_2\left(1 + \frac{\rho_i p_i |h_{i,i}|^2}{\sigma^2 + \rho_i\sigma_A^2 + \rho_i \sum_{j=1,j\neq i}^{N} p_j |h_{j,i}|^2}\right), \quad (1)$$

where $\vec{p} = \{p_1, p_2, \ldots, p_N\}$ and $\vec{\alpha} = \{\alpha_1, \alpha_2, \ldots, \alpha_N\}$. On the other hand, the total energy harvested at the D2D at receivers is given by

$$E(\vec{p},\vec{\rho}) = \sum_{i=1}^{N}\left((1-\rho_i)\,\eta_i \sum_{j=1}^{N} p_j |h_{j,i}|^2\right), \quad (2)$$

where η_i is the energy conversion efficiency of the D2D pair i. Based on (1) and (2), we build an objective function that expresses the weighted sum of the achievable spectral efficiency and total energy harvesting, which is given by

$$U(\vec{p},\vec{\rho}) = \alpha\frac{R(\vec{p},\vec{\rho})}{R_{\max}} + (1-\alpha)\frac{E(\vec{p},\vec{\rho})}{E_{\max}}, \quad (3)$$

where α is a weighting parameter ranging from 0 to 1 and is used to determine the importance between information reception and energy harvesting on system objective. In addition, $R_{\max}$ and $E_{\max}$ are the maximum values of the achievable spectral efficiency and total energy harvesting, respectively, for a given network topology. It is noted that, because $E(\vec{p},\vec{\rho})$ is a linear function, the maximum of energy harvested under a given network topology is obtained as $E_{\max} = E(\vec{P}_{\max}, \vec{0})$. On the other hand, it is difficult to intuitively determine the maximum achievable spectral efficiency because $R(\vec{p},\vec{\rho})$ is an non-convex function due to the interference term. Therefore, $R_{\max}$ for a given network topology is obtained using an ES algorithm. Since SWIPT systems transmit data and energy at the same time, both the SE for data and EH performance for energy are important. Thus, the use of the weight factor α has advantage in that it can adjust more (less) weight to more (less) important indicators.

Then, we can construct the optimization problem that finds the optimal transmit power and power-splitting ratio to maximize the objective function, as given by

$$\max_{\vec{p},\vec{\rho}} \quad U(\vec{p},\vec{\rho})$$
$$\text{s.t.} \quad 0 \leq p_i \leq P_{\max},$$
$$0 \leq \rho_i \leq 1, \quad \text{for } 1 \leq i \leq N, \quad (4)$$

where $P_{\max}$ is the maximum transmit power of D2D transmitters.

III. Iterative Searching Algorithms

In this section, we introduce ES and GS with a barrier function to numerically find the global optimum and sub-optimum values of $\vec{p}$ and $\vec{\rho}$ for the non-convex optimization problem.

A. Exhaustive Search

The ES algorithm is a general method used to find the global optimal point, and involves systematically enumerating all the possible candidates for the solution and verifying whether each candidate satisfies

Algorithm 1: Gradient Search Algorithm.

initialize p_i, ρ_i randomly in feasible region
set β_p, β_ρ and ϵ
repeat :
  $\vec{p}_{old} = p$ and $\vec{\rho}_{old} = \rho$
  $\vec{p} = \vec{p}_{old} + \beta_p \times \frac{\partial \mathcal{B}}{\partial \vec{p}}$
  $\vec{\rho} = \vec{\rho}_{old} + \beta_\rho \times \frac{\partial \mathcal{B}}{\partial \vec{\rho}}$
until $||\mathcal{B}(\vec{p}, \vec{\rho}) - \mathcal{B}(\vec{p}_{old}, \vec{\rho}_{old})|| < \epsilon$

the problem statement. The control parameters, $\vec{p}$ and $\vec{\rho}$, are quantized with M equally spaced lengths, and all possible combinations of the quantized parameters are examined to determine the maximum value of the objective function. It is to be noted that the maximum value under ES approaches the global optimum as M goes infinity with an exponentially increasing time complexity of $O(M^{2N})$.

B. Gradient Search With Barrier

GS, also known as the steepest ascent/descent method, is the simplest and most fundamental optimization method used for unconstrained optimization. In the case of constrained optimization, we can define the continuous and differentiable barrier function whose values at the boundaries of the feasible region increase to infinity. The barrier function is used to replace inequality constraints by adding a penalizing term in the objective function [21]. With the barrier function, the constrained optimization becomes unconstrained, and the objective function can be optimized more easily. In this work, we employ a log barrier function, whose value at a point increases to infinity as the point approaches the boundary of the feasible region of the objective function $\mathbb{R}_+^{2N}$. Together with the constraints of $0 < p_i \leq P_{\max}$ and $0 \leq \rho_i \leq 1$, the log barrier function is given by

$$\psi(\vec{p}, \vec{\rho}) = \frac{1}{t} \sum_{i=1}^{N} [\log(P_{\max} - p_i) + \log p_i + \log(1 - \rho_i) + \log \rho_i], \tag{5}$$

where $t > 0$ is a parameter of the barrier. Using (5), we build a new objective function with a barrier given by

$$\mathcal{B}(\vec{p}, \vec{\rho}) = U(\vec{p}, \vec{\rho}) + \psi(\vec{p}, \vec{\rho}). \tag{6}$$

To obtain the optimal solution for (6), we use the simple GS technique. Algorithm 1 explains the GS for $\mathcal{B}(\vec{p}, \vec{\rho})$, where β_p and β_ρ are the step sizes for updating $\vec{p}$ and $\vec{\rho}$, respectively, and ϵ is a tolerance coefficient. It is noted here that we use two different step sizes, i.e., β_p and β_ρ to facilitate the fast convergence of the algorithm, because the available range of $\vec{p}$ is quite different from that of $\vec{\rho}$. The time complexity of the GS algorithm has the upper bound of $O(\epsilon^{-2})$ [22], [23].

IV. DNN-Based Learning Algorithm

In this section, we propose a DNN-based learning algorithm to approximate the optimal values of $\vec{p}$ and $\vec{\rho}$ for the non-convex optimization problem of (4). Fig. 3 shows the proposed DNN model with L hidden layers, the weight matrix set $\mathbf{W} = \{W^{(0)}, W^{(1)}, \ldots, W^{(L)}\}$ and the bias vector set $\mathbf{B} = \{\vec{b}^{(0)}, \vec{b}^{(1)}, \ldots, \vec{b}^{(L)}\}$. Together with the input bias vector $\vec{b}^{(0)}$, the vector of channel gains among N D2D pairs $\vec{h} \in \mathbb{R}^{N^2}$ is used as the input data whose $(N(i-1)+j)$-th element corresponds to $|h_{i,j}|^2$ for $1 \leq i, j \leq N$. The hidden layer is composed of L layers, and each of them has N^2 nodes, which are of the same size as $\vec{h}$.

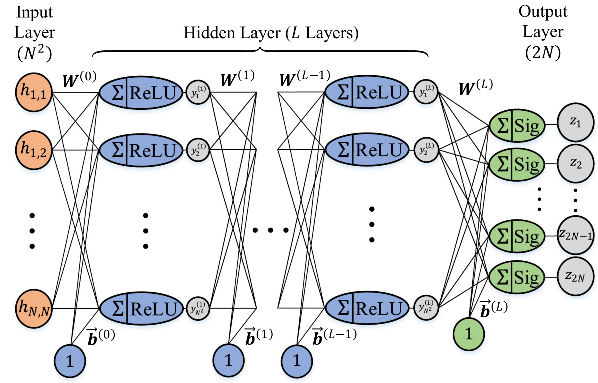


Fig. 2. Proposed deep neural network design.

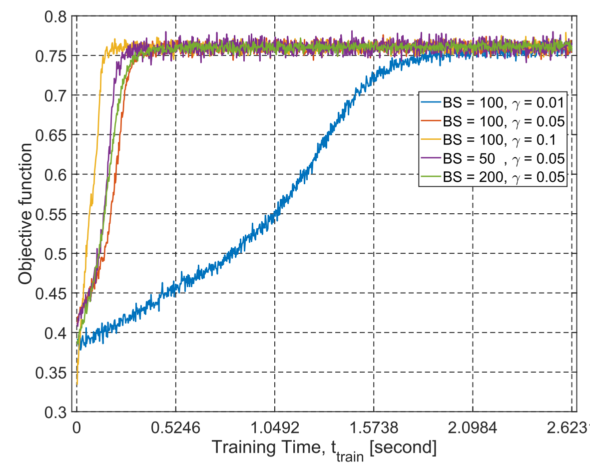


Fig. 3. Convergence speed of the DNN-based algorithm.

With the input vector, $\vec{y}^{(1)} \in \mathbb{R}^{N^2 \times 1}$ is calculated at the nodes of the first hidden layer, which is given by

$$\vec{y}^{(1)} = \left[W^{(0)}\vec{h} + \vec{b}^{(0)}\right]^+ \tag{7}$$

where $W^{(0)} \in \mathbb{R}^{N^2 \times N^2}$, $\vec{b}^{(0)} \in \mathbb{R}^{N^2 \times 1}$, and $[\cdot]^+ = \max(0, \cdot)$ indicates the rectified linear unit (ReLU) function. $\vec{y}^{(l)}$ for $1 < l \leq L$ is computed by

$$\vec{y}^{(l)} = \left[W^{(l-1)}\vec{y}^{(l-1)} + \vec{b}^{(l-1)}\right]^+, \tag{8}$$

where $W^{(l-1)} \in \mathbb{R}^{N^2 \times N^2}$ and $\vec{b}^{(l-1)} \in \mathbb{R}^{N^2 \times 1}$. $\vec{y}^{(l)}$ is forwarded to next hidden layer. At the output layer, the output vector $\vec{z} \in \mathbb{R}^{2N \times 1}$ is obtained by

$$\vec{z} = g\left(W^{(L)}\vec{y}^{(L)} + \vec{b}^{(L)}\right), \tag{9}$$

where $W^{(L)} \in \mathbb{R}^{2N \times N^2}$, $\vec{b}^{(L)} \in \mathbb{R}^{2N \times 1}$, and $g(x) = \frac{1}{1+e^{-x}}$ is a sigmoid function. With this output vector $\vec{z}$, $\vec{p}$ and $\vec{\rho}$ are determined by

$$\vec{p} = P_{\max} \cdot \vec{z}_{[1:N]}, \ \vec{\rho} = \vec{z}_{[N+1:2N]}. \tag{10}$$

In order to find the optimal values of $\vec{p}$ and $\vec{\rho}$, it is important to determine an appropriate loss function to learn the weight matrices $W^{(l)}$ and bias vectors $\vec{b}^{(l)}$ for given input data $\vec{h}$. Usually, the loss function is defined as a negative objective function, which is given by

TABLE I
COMPUTATIONAL COMPLEXITY COMPARISON ($N = 10$)

Algorithm	Computation complexity	The number of operations
ES	$O\left(M^{2N}\right)$	10^{60}
GS	$O\left(\epsilon^{-2}\right)$	10^{10}
DNN	$O\left(LN^4\right)$	10^6

$L_{old}(\vec{p}, \vec{\rho}) = -U(\vec{p}, \vec{\rho})$ [12]. However, from the numerous simulation trials, it has been revealed that the performance of the DNN using this conventional loss function is severely degraded in the interference-limited environment. So, we newly build the loss function considering the interference strengths among D2D pairs. Inspired by the fact that it is optimal for maximizing a weighted sum rate to allocate most of the communication resources to the node with the best channel condition in the interference-limited environment [24], we introduce a weight parameter reflecting the interference level of each D2D pair, which is given by

$$\omega_i = \left(\frac{|h_{i,i}|^2}{\sum_{j=1, j\neq i}^{N} |h_{j,i}|^2}\right) \Bigg/ \left(\frac{\mu_{i,i}}{\sum_{j=1, j\neq i}^{N} \mu_{j,i}}\right). \tag{11}$$

It is noted that the weight ω_i is designed to decrease (increase) the rate of a node having strong (weak) interference, compared to the mean channel gain $\mu_{i,i}$. By applying this weight ω_i to the rate r_i, we obtain the weighted spectral efficiency as $R_w(\vec{p}, \vec{\rho}) = \sum_{i=1}^{n} \omega_i r_i$. Then, we use the modified loss function given by

$$L_{new}\left(\vec{p}, \vec{\rho}\right) = -\alpha \frac{R_w\left(\vec{p}, \vec{\rho}\right)}{R_{\max}} - (1-\alpha)\frac{E\left(\vec{p}, \vec{\rho}\right)}{E_{\max}}. \tag{12}$$

From the matrix and vector multiplications, the computational time complexity of the proposed DNN is $O(LN^4)$ [23], in which the computational complexity for training DNN is not included.[1] Table I summarizes the comparisons of the computational complexities of ES, GS, and DNN. For better understanding, we provide an example to evaluate the computational complexity of the three algorithms when $M = 1000$, $\epsilon = 10^{-5}$, $L = 10$, and $N = 10$. From the results, it is confirmed that the DNN can reduce the computational complexity remarkably, when compared to the ES and GS algorithms.

V. PERFORMANCE EVALUATION

For performance evaluation, we vary N and $P_{\max}$ from 3 to 7 and 11 to 32 dBm, respectively. Base-band noise power spectrum, additional white Gaussian noise power spectrum, and conversion factor are set to $\sigma^2 = -70$ dBm, $\sigma_A^2 = -100$ dBm, and $\eta = 50\%$, respectively [18]–[20]. To generate the wireless channels, we define the channel gain between nodes i and j as $|h_{i,j}|^2 = \frac{g_{i,j}}{d_{i,j}^m}$, where $d_{i,j}$ is the physical distance between two nodes, m is the path-loss exponent, and $g_{i,j}$ is the Rician small scale fading gain with 5 dB K-factor. Considering the practical network environment in which the feasible distance for energy harvesting is short (less than tens of meters) [29], we set $d_{i,j}$ for the direct link and interference link to follow the normal distribution with the average of 10 m and 20 m, respectively, with path-loss exponent $m = 3.6$, which grants random deployment of D2D pairs in a cell. The quantization parameter $M = 10^3$ is used for ES. For GS, we use the parameter of barrier function $t = 10^2$, tolerance coefficient $\epsilon = 10^{-5}$ and step length factors $\beta_p = P_{\max}/10^3$ and $\beta_\rho = 1/10^3$. For the implementation of the DNN-based algorithm, we use Python 3.6 with TensorFlow 1.14 library on a computer with Intel i5-6500 CPU, one NVIDIA GeForce RTX 2080 Ti GPU, and 16 GB memory. We use the gradient descent optimizer to update the weight $\mathbf{W}$ and the bias $\mathbf{b}$, and set the number of hidden layers to $L = 10$. Because the structure of the proposed DNN algorithm should be changed according to the number of D2D pairs, we build as many DNNs as the number of D2D pairs and train them in an offline using randomly generated 10^5 channels for each DNN. After that, the results of each neural network are stored in each device to determine $\vec{\rho}$ and $\vec{p}$. All the simulation results of ES, DNN, and GS are obtained through Monte Carlo simulations with 10^3, 10^4 and 10^4 iterations, respectively.

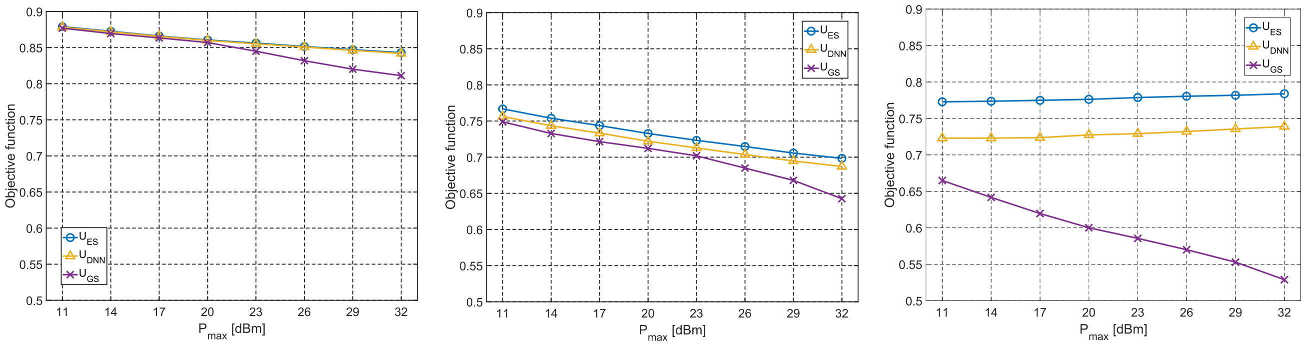
Fig. 3 compares the convergence speed of the proposed DNN-based algorithm, upon varying the batch size (BS) and learning rate (γ). In the results, we can verify the well-known fact that the employment of a low learning rate ensures the convergence of the algorithm at the expense of longer convergence time. Furthermore, the result shows that the convergence time of the DNN algorithm is the shortest, with the batch size of 100. Therefore, in our work, we use the learning rate of 0.1 and batch size of 100 for simulating the DNN-based algorithm.

Fig. 4 shows the convergence results of the objective function for ES, DNN, and GS as a function of $P_{\max}$ with three D2D pairs for $\alpha \in \{0.25, 0.5, 0.75\}$. There is a clear trade-off relationship between energy harvesting and spectral efficiency, which means that, as the transmission power increases, the energy harvesting of D2D pairs increases and spectral efficiency decreases. This result shows that the value of the objective function decreases as $P_{\max}$ increases for $\alpha = 0.25$ and 0.5, which explains that the degree of deterioration in spectral efficiency is greater than the degree of improvement in energy harvesting. On the other while, the objective function value slightly increases for $\alpha = 0.75$, which shows that the degree of deterioration in spectral efficiency is slightly smaller than or almost equal to the degree of improvement in energy harvesting. It is noted here that the results of the DNN are much closer to those of ES than to those of GS, which shows the near-global optimality of the DNN-based optimization method.

Fig. 5 shows the convergence value of the objective function for ES, DNN and GS as a function of the number of D2D pairs with $\alpha \in \{0.25, 0.5, 0.75\}$ and $P_{\max} = 32$ dBm. As the number of D2D pairs increases, energy harvesting increases but interference from the other pairs decreases spectral efficiency. The result proves that as the number of D2D pairs increases, the degree of improvement in energy harvesting is greater than the degree of deterioration in spectral efficiency, which yields an increase in the objective function value. It is noted here that the performance gap between ES and the proposed DNN becomes larger because of the non-convexity of SE but the results of the proposed DNN are very close to that of ES.

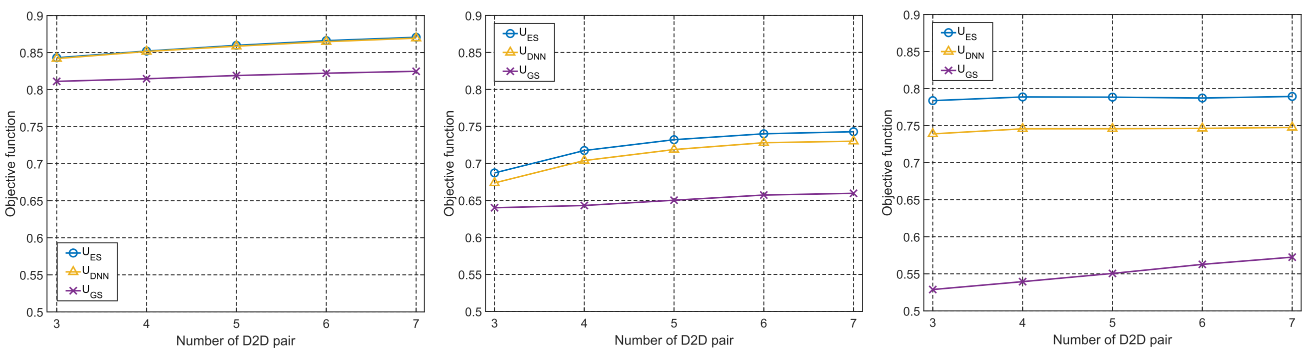
Fig. 6 shows the convergence value of the objective function for ES, DNN and GS, upon varying α with the granularity of 0.05, assuming three D2D pairs and $P_{\max} = 32$ dBm. This figure shows that, when α is close to 0 or when the energy harvesting term dominates the objective function, the convergence values of the objective function for DNN and GS are almost similar to that of ES because of the linearity of the energy-harvesting term. On the other hand, when the objective function is dominated by spectral efficiency, we can obtain only sub-optimal solutions for GS and DNN, because of the non-convexity of the spectral efficiency term; nevertheless, the performance of DNN is much better than that of GS. It is noted that a simple calculation for the utility function using the trade-off relation between SE and EH shows that the

[1]The training of DNN can be executed in an offline, i.e., a server uses a parallel computation with graphical processing unit for training. Then, each Tx-Rx pair can use this trained DNN to determine $\overrightarrow{p}$ and $\overrightarrow{\rho}$ in real time depending on channel gain. For this reason, the training process of DNN is not included to calculate the computational complexity [25]–[28].



(a) (b) (c)

Fig. 4. Objective function value as a function of $P_{\max}$. (a) $\alpha = 0.25$. (b) $\alpha = 0.50$. (c) $\alpha = 0.75$.



(a) (b) (c)

Fig. 5. Objective function value as a function of the number of D2D pairs. (a) $\alpha = 0.25$. (b) $\alpha = 0.50$. (c) $\alpha = 0.75$.

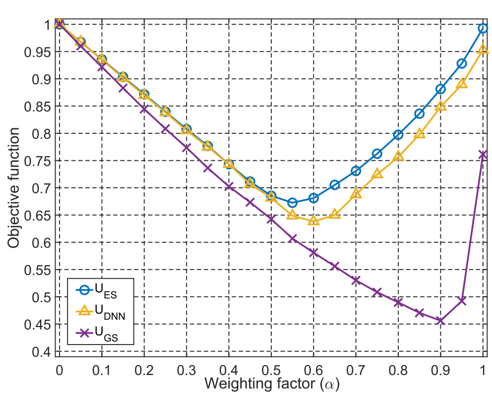


Fig. 6. Objective function value as a function of the dominant α.

objective function has the worst performance when α is at the middle of its range.

VI. Conclusion

In this work, we investigated the trade-off relationship between spectral efficiency and energy harvesting in a SWIPT-based D2D network with power-splitting policy. We built a non-convex optimization problem and solved it using both iteration-based methods (ES and GS with barrier function) and the newly designed DNN-based algorithm. From the results, we verified the trade-off between energy harvesting and spectral efficiency. As $P_{\max}$ or the number of D2D pairs increases, the amount of energy harvested increases while the spectral efficiency decreases. Furthermore, we verified that the degree of improvement in energy harvesting is greater (lesser) than the degree of deterioration of the spectral efficiency as the number of D2D pairs ($P_{\max}$) increases. The results revealed that the DNN-based algorithm achieves near-global optimality with reduced time complexity compared to the optimization-based iterative algorithms. As a future work, we plan to study the optimization of power allocation for the SWIPT technique by considering the time-switching and the hybrid time-switching and power splitting techniques. Furthermore, we will extend our work to include the effect of D2D pairs on the cellular network which shares the same bandwidth with the D2D network.

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