Fast Specific Absorption Rate Aware Beamforming for Downlink SWIPT via Deep Learning

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***Abstract*—This paper investigates fast implementation of the optimal transmit beamforming design for simultaneous wireless information and power transfer in the multiuser multiple-input-single-output downlink with specific absorption rate (SAR) constraints. The problem of interest is to maximize the received signal-to-interference-plus-noise ratio and the energy harvested for all receivers, while satisfying the transmit power and the SAR constraints. The optimal solutions can be obtained via convex optimization and bisection search but with high complexity. To reduce the computational complexity, this paper proposes the deep learning technique to predict key features of the problem and then recover the beamforming solutions with much reduced complexity. Simulation results demonstrate that our proposed algorithms can significantly reduce the algorithm execution time while maintaining satisfactory performance.**

I. Introduction

Simultaneous wireless information and power transfer (SWIPT) is a new technology where information and energy flows co-exist, co-engineered to simultaneously provide communication connectivity and energy sustainability [1], [2]. From the seminal work of Varshney [3], who introduced the concept of SWIPT and the fundamental trade-off between information and energy transfer, substantial works appear in the literature that study SWIPT from different perspectives.

On the other hand, wireless technologies are subject to strict regulations on the level of radio-frequency (RF) radiation that users of the terminals are exposed to. Two widely adopted regulations/measures on RF exposure are mainly considered. The first one is the maximum permissible exposure (MPE) in [W/m^2], which is defined as the highest level of electromagnetic radiation to which a user may be exposed without incurring an established adverse health effect. The second one is the specific absorption rate (SAR) that measures the absorbed power in a unit mass of human tissue by using units of Watt per kilogram [W/kg]. For instance, the Federal Communications Commission (FCC) enforces an SAR limitation of 1.6 W/kg averaged over one gram of tissue on partial body exposure [4].

The SAR constraints are incorporated into the transmit signal design for a multiple-input multiple-output (MIMO) uplink channel in [5] and [6], and the SAR-aware beamforming and transmit signal covariance optimization methods are presented in [7] and [8], respectively. However, the integration of SAR exposure constraints in the design of SWIPT systems is unexplored, although SWIPT may significantly contribute to the electromagnetic pollution (electrosmog). For example, one of the main applications of SWIPT is for medical devices in wireless body area networks, where an access point will support the communication connectivity and the power sustainability of a short-range sensor network in, on, or around the human body [9].

In this paper, we focus on the power splitting (PS) approach [10] and study the beamforming design in a multiuser multiple-input single-output (MISO) downlink channel, where the receivers are characterized by both communications quality-of-service (QoS) and energy harvesting (EH) constraints with additional SAR limitations; the nonlinearity of the rectification circuit is also taken into account. Similar problems have been studied in [11] and [12] for an interference channel and a downlink MISO channel, respectively, but without the consideration of SAR constraints and nonlinearity of EH. In our previous work [13], we have derived the optimal beamforming and power splitting solutions by leveraging semidefinite programming (SDP) together with rank relaxation. However, the complexity of the optimal beamforming solution is high which makes it difficult to adapt to the channel variations and the users' requirements.

In this paper, we propose to use the deep learning technique to reduce the computational complexity of the optimal beamforming solutions. The rational is that the deep learning technique trains neural networks offline and then deploys the trained neural networks for fast online optimization. The computational complexity is transferred from the online optimization to the offline training. Deep learning has been widely used in optimization tasks of wireless resource management, and early works use deep neural networks (DNNs) mainly to predict transmit power [14], [15], and later to directly estimate the beamforming matrix [16]–[20]. Most existing works do not exploit the problem structure which will lead to high training complexity and poor prediction performance when the numbers of transmit antennas and users increase.

We propose to combine deep learning with exploitation of expert knowledge specific to the beamforming problems to quickly infer the solution, as an application of our recently proposed framework of beamforming neural networks [21], [22] to the area of SWIPT with SAR constraints. This method improves the learning accuracy compared to the existing data-driven approaches by specifying the best features to be learned with reduced dimension. Our simulation results show that the proposed solutions can significantly reduce the computational time compared to the optimal solution and even the heuristic

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solution with satisfactory performance, and outperform the data-driven approach that directly predicts the beamforming solution.

The remainder of this paper is organized as follows. Section II introduces the system transmission model and problem formulation. In Section III, we propose two fast deep learning based algorithms to solve the SAR-aware beamforming. Simulation results are provided to confirm the proposed algorithms in IV and our work is concluded in Section V.

Notation: All boldface letters indicate vectors (lower case) or matrices (upper case). The superscripts $(\cdot)^\dagger$ and $(\cdot)^{-1}$ denote the conjugate transpose and the matrix inverse, respectively. The identity matrix is denoted by $\mathbf{I}$. $\|\mathbf{z}\|$ denotes the L_2 norms of a complex vector $\mathbf{z}$. $\mathrm{Tr}(\mathbf{A})$ denotes the trace of a matrix $\mathbf{A}$, while $\mathbf{A} \succeq 0$ indicates that matrix $\mathbf{A}$ is positive semidefinite.

II. System Model and Problem Formulation

A. System Model

We consider an MISO downlink channel consisting of an N_t-antenna transmitter (e.g., a base station (BS)) and K single-antenna receivers that employ single-user detection. The BS transmits with a total power P_T and let s_k be its transmitted data symbol to receiver k, which is Gaussian distributed with zero mean and unit variance. The transmitted data symbol s_k with normalized power is mapped onto the antenna array elements by the beamforming vector $\mathbf{w}_k \in \mathbb{C}^{N_t\times 1}$. The received baseband signal at receiver k can be expressed as

$$y_k = \underbrace{\mathbf{h}_k^\dagger \mathbf{w}_k s_k}_{\text{Information signal}} + \underbrace{\sum_{j\neq k} \mathbf{h}_k^\dagger \mathbf{w}_j s_j}_{\text{Interference}} + n_k, \tag{1}$$

where $\mathbf{h}_k \in \mathbb{C}^{N_t\times 1}$ is the channel between the BS and the k-th receiver and n_k denotes the additive white gaussian noise (AWGN) component with zero mean and variance N_0. Therefore, the received power at receiver k is equal to

$$P_k^r = \sum_{j=1}^{K} |\mathbf{h}_k^\dagger \mathbf{w}_j|^2 + N_0. \tag{2}$$

The receivers have RF-EH capabilities and therefore can harvest energy from the received RF signal based on the power splitting technique. With this approach, each receiver splits its received signal into two parts with a parameter $\rho_k \in (0,1)$: a) $100\rho_k\%$ of the received power is converted to a baseband signal for further signal processing and data detection, and b) the remaining is driven to the required circuits for conversion to DC voltage and energy storage. During the baseband conversion, additional circuit noise, v_k, is present due to phase offsets and non-linearities which is modeled as AWGN with zero mean and variance N_C. The signal-to-interference-plus-noise ratio (SINR) metric characterizing the data detection process at the k-th receiver is given by

$$\Gamma_k = \frac{\rho_k |\mathbf{h}_k^\dagger \mathbf{w}_k|^2}{\rho_k \left(N_0 + \sum_{j\neq k} |\mathbf{h}_k^\dagger \mathbf{w}_j|^2\right) + N_C}. \tag{3}$$

On the other hand, the total power that can be harvested is equal to $P_k^S = F((1-\rho_k)P_k^r)$, where $F(\cdot)$ is a non-linear parametric EH function which will be presented later.

As discussed, wireless communication devices are subject to SAR limitations. Previous reported results such as [6] have shown that the pointwise SAR value with multiple transmit antennas can be modeled as a quadratic form of the transmitted signal, and the SAR matrix fully describes the SAR measurement's dependence on the transmitted signals; entries of the SAR matrix have units of W/kg. Because the SAR measurements are always real positive numbers, the SAR matrices are positive-definite conjugate-symmetric matrices.

Since SAR is a quantity averaged over the transmit signals for a specific human tissue, we model the l-th SAR constraint with a time-averaged quadratic constraint given by

$$\mathrm{SAR}_l = \mathbb{E}_{\{s_k\}} \mathrm{Tr}\left(\sum_{k=1}^{K} s_k^\dagger \mathbf{w}_k^\dagger \mathbf{A}_l \mathbf{w}_k s_k\right) = \sum_{k=1}^{K} \mathbf{w}_k^\dagger \mathbf{A}_l \mathbf{w}_k \le P_l, \tag{4}$$

where $\mathbf{A}_l \succeq \mathbf{0}$ is the l-th SAR matrix and P_l is the l-th SAR limit.

B. Problem Formulation

We study the following problem of maximizing the ratios of the received SINR and EH over the target requirements, i.e., $\max\left\{\frac{\Gamma_1}{\bar\gamma_1}, \cdots, \frac{\Gamma_k}{\bar\gamma_k}, \cdots, \frac{\Gamma_K}{\bar\gamma_K}, \frac{P_1^S}{\bar\lambda_1}, \cdots, \frac{P_k^S}{\bar\lambda_k}, \cdots, \frac{P_K^S}{\bar\lambda_K}\right\}$ subject to the SAR and total power constraints, where $\bar\gamma_k, \bar\lambda_k$ are the SINR and the EH requirements, respectively. This choice of the objective function will balance the received SINR and the EH between users. To make the problem more tractable, we introduce an auxiliary variable t, and formulate the optimization problem in **P1** where P_T is the maximum total transmit power, and L is the number of SAR constraints. $F(x)$ is output DC power at the k-th receiver represented by a nonlinear function and x is the input RF power.

$$\mathbf{P1:} \quad \max_{\{\mathbf{w}_k, \rho_k, t\}} \ t \tag{5}$$

$$\text{s.t.} \quad \frac{|\mathbf{h}_k^\dagger \mathbf{w}_k|^2}{\sum\limits_{j=1, j\neq k}^{K} |\mathbf{h}_k^\dagger \mathbf{w}_j|^2 + N_0 + \frac{N_C}{\rho_k}} \ge t\bar\gamma_k \triangleq \gamma_k, \tag{6}$$

$$F\left((1-\rho_k)\left(\sum_{j=1}^{K} |\mathbf{h}_k^\dagger \mathbf{w}_j|^2 + N_0\right)\right) \ge t\bar\lambda_k \triangleq \tilde\lambda_k, \tag{7}$$

$$0 \le \rho_k \le 1, \forall k,$$

$$\sum_{k=1}^{K} \mathbf{w}_k^\dagger \mathbf{A}_l \mathbf{w}_k \le P_l, \forall l, \tag{8}$$

$$\sum_{k=1}^{K} \|\mathbf{w}_k\|^2 \le P_T.$$

The nonlinear EH function can take many forms to capture the relationship between the input and output power at the energy receiver, such as the sigmoid function [23], the linear fraction [24] and a heuristic expression by curve fitting [25]. In general, the nonlinear EH function is monotonically increasing, therefore we can find the inverse mapping $F^{-1}(\cdot)$, and the EH constraint (8) can be rewritten as

$$(1-\rho_k)\left(\sum_{j=1}^{K}|\mathbf{h}_i^\dagger \mathbf{w}_k|^2 + N_0\right) \geq F^{-1}(\tilde{\lambda}_k) \triangleq \lambda_k. \tag{9}$$

It is difficult to solve the above problem **P1**, because both SINR and EH constraints (6) and (7) are nonconvex, and we also have additional multiple SAR constraints. In our previous work [13], we have shown that the optimal solution to **P1** can be found by solving the power minimization problem **P2** below:

$$\textbf{P2:} \min_{\{\mathbf{W}_k,\rho_k\}} \quad \sum_{k=1}^{K} \mathrm{Tr}(\mathbf{W}_k) \tag{10}$$

$$\text{s.t.} \quad \frac{\mathbf{h}_k^\dagger \mathbf{W}_k \mathbf{h}_k}{\sum_{j=1}^{K} \mathbf{h}_k^\dagger \mathbf{W}_j \mathbf{h}_k + N_0 + \frac{N_k}{\rho_k}} \geq \frac{\gamma_k}{1+\gamma_k},$$

$$\sum_{j=1}^{K} \mathbf{h}_k^\dagger \mathbf{W}_j \mathbf{h}_k + N_0 \geq \frac{\lambda_k}{1-\rho_k},$$

$$0 \leq \rho_k \leq 1, \mathbf{W}_k \succeq \mathbf{0}, \forall k,$$

$$\sum_{k=1}^{K} \mathrm{Tr}(\mathbf{A}_l \mathbf{W}_k) \leq P_l, \forall l. \tag{11}$$

where have defined new matrix variables $\mathbf{W}_k = \mathbf{w}_k \mathbf{w}_k^\dagger, \forall k$. To be specific, if **P1** is solved and the optimal t^* is achieved, then the same beamforming and power splitting solutions are also optimal for **P2** to achieve the same SINR and EH, and the optimal minimum power will be P_T. Because **P1** is a quasiconvex problem in t, once **P2** is solved, **P1** can be solved via the bisection search Algorithm. Therefore, in the rest of the paper we will focus on solving the problem **P2**.

III. Deep Learning Based Solutions

A. The General Structure

Our proposed deep learning-based structure for the beamforming optimization is shown in Fig. 1. Existing data-driven approaches directly predict the beamforming matrix with NK complex elements which may lead to inaccurate and even under-fitting results that cannot guarantee the end performance. To tackle this challenge, the main idea of our proposed deep learning structure is to predict only the main features of the problem with reduced dimension, and then find the beamforming solution in a fast way using these features. Therefore it includes two main modules: the neural network module and beamforming recovery module.

We choose the convolutional neural network (CNN) layers followed by the feedforward layer as the base of the neural network module, because the CNN has strong ability of extracting features. In addition, the CNN can reduce the number of learned parameters by sharing weights and biases. To overcome the challenge of predicting the beamforming matrix directly, we propose to predict some chosen key features extracted from the problem structure, which is much less than the number of elements in the beamforming matrix. The beamforming recover module will then find the beamforming solution according to the expert knowledge specific to the problem and the learned features.

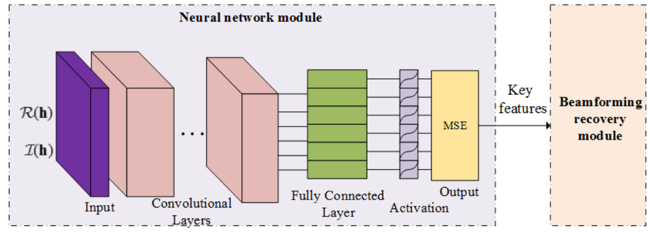

Fig. 1. The neural network structure of the proposed deep learning solutions.

The complex channel coefficients are fed into the neural network module to predict the key features as output, but complex inputs are not yet supported by standard neural network software. To deal with this issue, we separate the complex channel vector into the in-phase component $\Re(\mathbf{h})$ and quadrature component $\Im(\mathbf{h})$.

Here we propose two learning algorithms depending on the chosen features and the corresponding beamforming recovery methods.

B. Learning Algorithm 1

In the first learning algorithm, we choose the power splitting variables $\{\rho_k\}$ as the features to predict. The reason is that although the problem **P2** is convex, it does not belong to a specific category of standard convex programming problems such as SDP or second-order cone programming (SOCP) for which efficient algorithms exist because of the presence of $\{\rho_k\}$. If we predict the more computational demanding variables $\{\rho_k\}$, this will significantly reduce the overall complexity.

To recover the original beamforming solution, once $\{\rho_k\}$ are predicted, we can solve **P2** with the learned $\{\rho_k\}$ which becomes a standard SDP problem and can be more efficiently solved than the original **P2**. In this method, the number of real variables to predict is K.

C. Learning Algorithm 2

In the above method, the complexity of the beamforming recovery module is still relatively high because an SDP problem needs to be solved. In the second learning algorithm, we propose to predict more features so as to reduce the complexity of the recovery module. To be specific, we choose $\{\rho_k\}$ and some of the dual variables as the features. To this end, we first derive the dual problem of **P2** (given $\{\rho_k\}$) below:

$$\max_{\boldsymbol{\nu},\boldsymbol{\alpha},\boldsymbol{\beta}\geq 0} \quad -\sum_{l=1}^{L}\nu_l P_l + \sum_{k=1}^{K}\alpha_k\left(N_0 + \frac{N_i}{\rho_i}\right) + \sum_{k=1}^{K}\frac{\beta_k}{1-\rho_k}(\lambda_k - N_0)$$

$$\text{s.t.} \quad \mathbf{I} + \sum_{j=1}^{K}\theta_j \mathbf{h}_j \mathbf{h}_j^\dagger - \alpha_k\left(1+\frac{1}{\gamma_k}\right)\mathbf{h}_k \mathbf{h}_k^\dagger + \sum_{l=1}^{L}\nu_l \mathbf{A}_l \succeq \mathbf{0}, \forall k,$$

where $\boldsymbol{\nu}, \boldsymbol{\alpha}, \boldsymbol{\beta}$ are dual variables, and $\theta_k \triangleq \alpha_k - \beta_k$. Instead of learning all dual variables, we propose to choose the main features of $\{\theta_k\}, \{\nu_l\}$ and the primal variables $\{\rho_k\}$ to predict.

To recover the original beamforming solution, we first find the beamforming direction given by

$$\tilde{\mathbf{w}}_k = \frac{\left(\mathbf{I} + \sum_{j=1}^{K} \theta_j \mathbf{h}_j \mathbf{h}_j^\dagger + \sum_{l=1}^{L} \nu_l \mathbf{A}_l\right)^{-1} \mathbf{h}_k}{\| \left(\mathbf{I} + \sum_{j=1}^{K} \theta_j \mathbf{h}_j \mathbf{h}_j^\dagger + \sum_{l=1}^{L} \nu_l \mathbf{A}_l\right)^{-1} \mathbf{h}_k \|}. \quad (12)$$

With learned $\{\rho_k\}$ and $\{\tilde{\mathbf{w}}_k\}$, the remaining problem reduces to the power allocation problem **P3** to find $\{p_k\}$, which is a linear programming problem and much faster to solve than SDP, i.e.

$$\begin{aligned} \textbf{P3:} \quad \min_{\{p_k>0\}} \quad & \sum_{k=1}^{K} p_k && (13) \\ \text{s.t.} \frac{\rho_k G_{k,k} p_k}{\sum_{j=1}^{K} G_{k,j} p_j + \rho_k N_0 + N_C} & \geq \frac{\gamma_k}{1+\gamma_k}, \forall k, \\ (1-\rho_k)(\sum_{j=1}^{K} G_{k,j} p_j + N_0) & \geq \lambda_k, \forall k, \\ \sum_{k=1}^{K} p_k F_{k,l} & \leq P_l, \forall l. \end{aligned}$$

In this method, the number of real variables to predict is $2K + L$. As expected, it learns more features, so it will be faster to recover the original beamforming solution. This will be verified in the next section.

IV. Numerical Results

In this section, we carry out numerical evaluation of the performance of the proposed deep learning based beamforming solutions. We consider a MISO downlink consisting of K receivers randomly located around the BS with distance l_k and direction ζ_k drawn from the uniform distribution, $l_k \sim U(1,5)$ m and $\zeta_i \sim U(-\pi, \pi)$. Each receiver can harvest energy at frequency $f = 915$ MHz and it is assumed that the antenna gains at the BS and receivers are 8 dBi and 3 dBi, respectively. The path loss coefficient is 2.5. Because of the short distance between the BS and the receivers and dominance of the line-of-sight (LOS) signal, Rician fading is used to model the channel and the Rician factor is 5 dB. We consider a system consisting of one BS with three antennas serving two receivers and one SAR constraint, i.e., $K = 2, N_t = 3, L = 1$, $N_0 = -70$ dBm and $N_C = -50$ dBm, while the SINR and EH thresholds are the same for all receivers, i.e. $\bar{\Gamma}_k = \bar{\Gamma} = 10$ dB, $\bar{\lambda}_k = \bar{\lambda} = -15$ dBm, $\forall k$. We assume that the total transmit power constraint is $P_T = 2$ W. We use the nonlinear energy harvesting model below proposed in [24]

$$F(x) = \frac{\bar{a}x + \bar{b}}{x + c} - \frac{\bar{b}}{c}, \quad (14)$$

with fitted parameters $\bar{a} = 2.463, \bar{b} = 1.635, c = 0.826$. The SAR matrix is given below by [7]

$$\mathbf{A} = \begin{bmatrix} 0.35 & -0.64 - 0.15j & -0.17 + 0.32j \\ -0.64 + 0.15j & 2.51 & -0.31 + 0.29j \\ -0.17 - 0.32i & -0.31 - 0.29j & 2.32 \end{bmatrix}. \quad (15)$$

In our simulation, we generate 10,000 training samples and 1,000 testing samples with independent channels, respectively, using the optimal algorithm in [13]. We use four CNN layers each having 8 kernels with size 3×3 and the ReLU activation function. Adam optimizer [27] is used with the mean squared error based loss function. We will make comparisons with the optimal solution, the direct learning algorithm that predicts the beamforming matrix directly, and the zero-forcing (ZF) solution [13]. Note that unlike the previous works [11], [12] where closed-form ZF solutions exist when there is no SAR constraint, the SAR constraint does not permit a closed-form solution, therefore we use CVX [26] to solve the ZF solution, so its complexity is still high.

Figs. 2 depicts the average minimum achievable SINR and EH ratio by different investigated algorithms against the SAR. The performance of the proposed learned solution 1 is very close to that of the optimal solution, and significantly outperforms the ZF solution, while the performance of the proposed learned solution 2 is similar to but still outperforms that of the ZF solution. The direct learning method cannot guarantee satisfactory performance and is much worse than the ZF solution. Fig. 3 shows the feasibility of various schemes to satisfy both the SINR and the EH constraints (i.e., the value of the objective function of **P1** is greater than or equal to 1), which follows the similar trend as the results in Fig. 2.

In Fig. 4, we plot the percentage of the running time relative to the optimal solution for various schemes. We can see that both the ZF solution require similar time as the optimal solution. This is mainly because of solving variables $\{\rho_k\}$ incurs a high complexity. It is observed that the proposed learned solution 1 can save 35–40% of time compared to the the optimal solution while achieving near-optimal performance, and is much faster than the ZF solution. The proposed learned solution 2 can achieve nearly two orders of magnitude gain in running time, but still achieves better performance than the ZF solution.

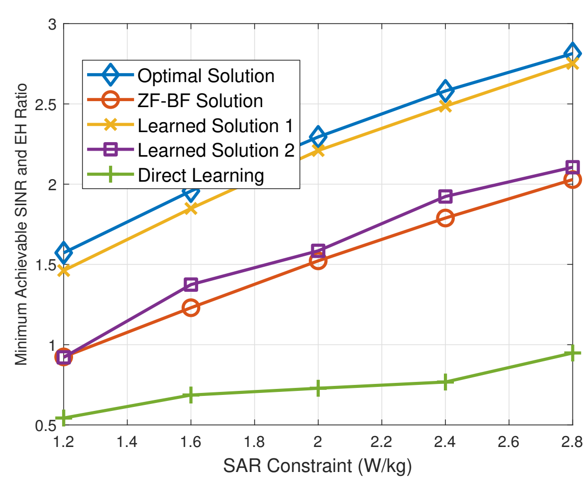

Fig. 2. The minimum achievable SINR and EH ratio vs SAR.

V. Conclusions

In this paper, we have studied the optimization of SAR-constrained multiuser transmit beamforming of a SWIPT

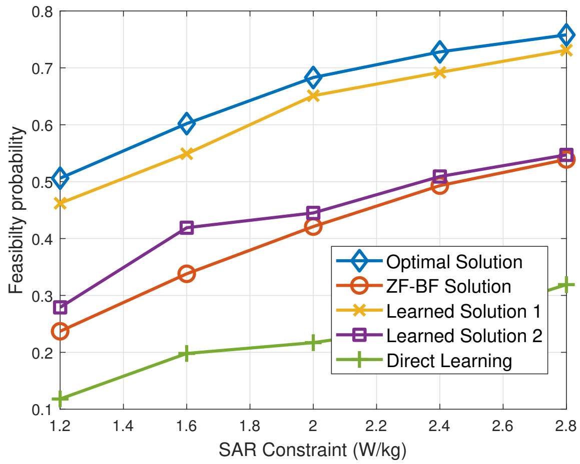

Fig. 3. The feasibility probability vs SAR.

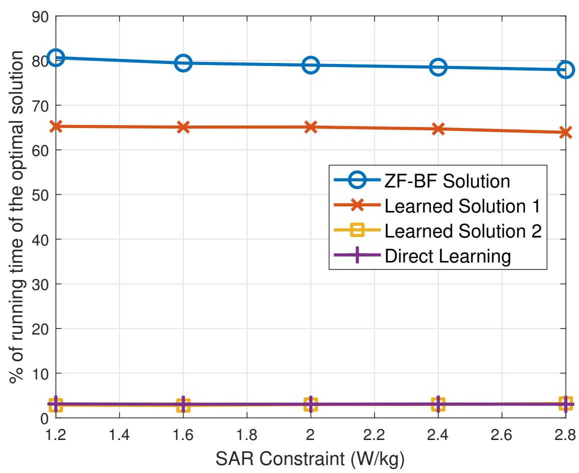

Fig. 4. The relative running time against that of the optimal solution vs SAR.

system. To reduce the complexity of finding the optimal beamforming and power splitting solutions, we designed two fast solutions using deep learning techniques which predict the main features of the optimization problem. Our simulation results have shown significant improvement of the proposed learning based solutions over the heuristic ZF solution and the direct learning approach. The findings demonstrate the potential of using deep learning to design fast beamforming solutions for SAR-aware SWIPT systems.

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