Deep Learning for Selection Between RF and VLC Bands in Device-to-Device Communication

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***Abstract*—This letter focuses on the selection between radio frequency (RF) and visible light communications (VLC) bands for users exchanging data directly with each other via device-to-device (D2D) communication. We target to maximize the energy efficiency of D2D communication while the outage is minimized. Since the VLC channel can vary quickly due to the possible changes in irradiance and incidence angles, we aim to reach a quick band selection decision in a multi-user scenario based only on the knowledge of the received power and sum interference from all D2D transmitters at the individual D2D receivers. The proposed solution is based on a deep neural network making an initial band selection decision. Then, based on the DNN's output, a fast heuristic algorithm is proposed to further improve the band selection decision. The results show that the proposal reaches a close-to-optimal performance and outperforms the existing solutions in complexity, outage ratio, and energy efficiency.**

***Index Terms*—Device-to-device, visible light communications, band selection, deep neural networks.**

I. Introduction

FUTURE mobile communications are expected to cope with the continuous increase in the amount of transmitted data resulting in a lack of available radio spectrum [1]. A suitable solution for an efficient use of the spectrum is device-to-device (D2D) communication allowing any pair of nearby D2D user equipment (DUE) to communicate directly and, hence, to improve the spectral efficiency and the system capacity [2]. To further enhance the system capacity, multiple D2D pairs can reuse the same radio frequency (RF) band [3]. Also, additional bands besides the RF licensed bands, such as Bluetooth or WiFi, can be exploited [4]. Another enticing option is to exploit visible light communications (VLC) operating at frequency bands of 400-790 THz. This makes VLC suitable for communicating at short distances, e.g., indoor [5].

Several studies demonstrate the benefits of the D2D communication using only VLC bands (e.g., [6]–[7]). Nevertheless, the VLC link may suffer from sudden drops in channel quality as it is highly susceptible to changes in the transmitter's ($\mathrm{DUE_t}$) irradiance and the receiver's ($\mathrm{DUE_r}$) incidence angles. Consequently, VLC links should not be implemented without an option to switch back to RF. An initial study on the combination of RF and VLC for D2D communication is presented in [1]. Then, in [8], an iterative two-phase heuristic algorithm is proposed to minimize the outage and to maximize the sum capacity of D2D pairs by selecting RF or VLC communication band for each pair. However, the solution in [8] relies on the assumption that channel gains among all DUEs in RF and VLC are known. Moreover, the band selection in [8] is based on an iterative algorithm, which is not suitable in dynamic scenarios, where a fast band selection is required.

To circumvent the need for the full channel knowledge, we present the band selection problem as a supervised binary classification problem targeting the selection of RF or VLC for every D2D pair. We assume only the knowledge of the received power and the received sum interference at each DUE_r in RF and VLC to minimize the outage and to maximize the average energy efficiency of the D2D communication. We solve this band selection problem via deep neural network (DNN). We choose DNNs as they make no prior assumptions on the data sets and give an instantaneous probabilistic output in a negligible time. Moreover, a trained DNN can be stored with low memory requirements while it still enables to extract a complex model/relation connecting its inputs and outputs as required by the nature of our problem.

To minimize the potential gap between the performance of the DNN exploiting limited channel knowledge among D2D pairs and the optimal case when full information is available, we design a low-complexity heuristic algorithm built upon the DNN's output to further improve the accuracy of the band selection. The algorithm relies on the probabilities of each D2D pair to communicate via RF (and VLC) obtained by the DNN, and copes with the inherent uncertainties in the DNN's decisions. Despite the proposed solution is of a very low complexity and requires only a limited knowledge of channels, the simulations demonstrate its close-to-optimal performance.

II. System Model and Problem Formulation

We assume N D2D pairs uniformly deployed in a square area. The RF (VLC) channel with a bandwidth B_R (B_V) is exploited by all D2D pairs communicating in RF (VLC). The D2D pairs using VLC are affected by the $\mathrm{DUE_t}$ irradiance and $\mathrm{DUE_r}$ incidence angles, which are generated randomly. Since any n-th D2D pair can communicate in either the RF or VLC band, we define a band indicator z^n. If the n-th D2D pair communicates over the RF band, z^n is set to 1, while if the n-th pair uses VLC, z^n is set to 0. Based on this, the

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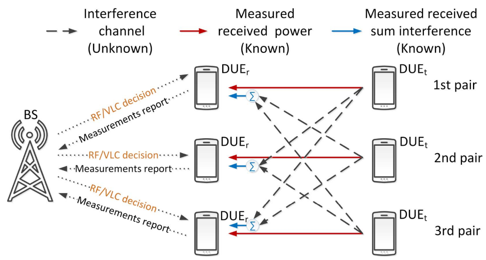


Fig. 1. System model.

energy efficiency of the n-th D2D pair is expressed as:

$$EE^n = \frac{C^n}{z^n(P_R^{t,n} + P_R^{r,n}) + (1 - z^n)(P_V^{t,n} P_V^{r,n})} \quad (1)$$

where $P_R^{t,n}$ and $P_V^{t,n}$ are the powers consumed by the n-th $\mathrm{DUE_t}$ during the transmission in RF and VLC, respectively; $P_R^{r,n}$ and $P_V^{r,n}$ are the powers consumed by the n-th $\mathrm{DUE_r}$ during the data reception in RF and VLC, respectively (the consumed powers in RF and VLC are modeled in line with [9] and [8], respectively); and C^n denotes the capacity of the n-th D2D pair defined as:

$$C^n = Blog_2(1 + \gamma^n) \quad (2)$$

where B is the communication channel bandwidth and γ^n is the signal to interference plus noise ratio (SINR). Considering the band indicator z^n, the bandwidth B in (2) is:

$$B = z^n B_R + (1 - z^n) B_V \quad (3)$$

Similarly, γ^n is calculated as:

$$\gamma^n = z^n \frac{p_R^n g_R^{n,n}}{N_R + \sum_{m \neq n} z^m p_R^m g_R^{m,n}} + (1 - z^n) \frac{p_V^n g_V^{n,n}}{N_V + \sum_{m \neq n} (1 - z^m) p_V^m g_V^{m,n}} \quad (4)$$

where p^n is the transmission power of the n-th D2D pair, $g^{n,n}$ is the channel gain between the $\mathrm{DUE_t}$ and the $\mathrm{DUE_r}$ of the n-th D2D pair, p^m is the transmission power of the m-th D2D pair that is inducing interference to the n-th D2D pair, $g^{m,n}$ is the channel gain between the $\mathrm{DUE_t}$ of the m-th pair and the $\mathrm{DUE_r}$ of the n-th pair, and N_R and N_V are the noises in RF and VLC, respectively. Note that, in VLC, the channel gains and the noise are functions of the users' directions (i.e., irradiance and incidence angles) and other parameters related to the LED and the photodetector in line with [10].

We consider that every n-th D2D pair requires an SINR satisfying $\gamma^n \geq \gamma^{th}$, where γ^{th} is the minimal SINR ensuring a reliable communication between the $\mathrm{DUE_t}$ and the $\mathrm{DUE_r}$. Thus, if $\gamma^n < \gamma^{th}$, the n-th D2D pair is considered to be in outage and the outage ratio is, then, calculated as:

$$\phi = N_o / N \quad (5)$$

where N_o represents the number of D2D pairs in outage.

We further assume that all D2D pairs transmit a VLC reference signal at the same time to measure the VLC communication quality [8] (similarly to the RF band, where the reference signals are used to measure the communication quality [11]). Moreover, the $\mathrm{DUE_r}$ of every n-th D2D pair measures the received power from its corresponding transmitter (i.e., $p_R^n g_R^{n,n}$ and $p_V^n g_V^{n,n}$) and the sum interference induced by all other transmitters (i.e., $\sum_{m \neq n} p_R^m g_R^{m,n}$ and $\sum_{m \neq n} p_V^m g_V^{m,n}$) based on existing reference signals in RF and VLC. The reference signals are conventionally exploited in mobile networks and our solution requires no additional signaling to obtain the required information. Also, the assumption on the knowledge of the received powers and sum interferences is in line with 3GPP recommendations related to the reported RSRP/RSRQ in the conventional networks [12]. The measured received power and the sum interference are reported to and processed in a centralized unit (e.g., a nearby base station).

This letter aims to solve the multi-objective optimization problem of minimizing the outage ratio (i.e., ϕ) and maximizing the average energy efficiency (i.e., $EE = \sum_{n=1}^{n=N} EE^n / N$) by selecting either RF or VLC band for each D2D pair. The problem is formulated as:

$$\begin{aligned} \mathbf{Z}^* = \ & \underset{\mathbf{Z}}{\operatorname{argmax}} \ \left(-\phi, \sum_{n=1}^{n=N} \frac{EE^n}{N}\right) \\ & \text{s.t.} \quad z^n \in \{0, 1\} \forall n \in \{1, \dots, N\} \ (a) \end{aligned} \quad (6)$$

The optimization problem in (6) is discrete with multiple non-linear objective functions and, thus, this problem is hard to solve. The problem can be solved sequentially by an exhaustive search if the outage minimization is selected as the objective with a higher priority than the energy efficiency maximization. First, a set of solutions achieving the minimal possible ϕ is determined. Second, the solution maximizing EE is selected out of the solutions obtained in the first phase. However, the exhaustive search is not feasible for practical implementation due to its very high complexity equal to $\mathcal{O}(2^N)$. Therefore, in the next section, we propose a novel DNN-based approach to select RF or VLC for each D2D pair.

III. Proposed Band Selection Scheme

DNNs have proven their efficiency in solving various mobile networks-related problems, such as, binary power control [13], channel prediction [14], or antenna selection [15], just to name a few. This efficiency is justified by the ability of the DNNs to obtain an output (and make a decision) instantly in a single step. The decision whether RF or VLC should be used by individual D2D pairs, as targeted in this letter, depends on the individual channel gains among all DUEs. However, to alleviate the problem of the high signaling required to obtain the individual channel gains among all DUEs (as assumed, e.g., in [8]), we consider that only the received powers and the received sum interferences in RF and VLC are known. With such information, it is not possible to determine individually the level of interference caused by one D2D pair to another D2D pair. Therefore, there is no possibility to extract analytically the relation of the received power and the received sum interferences to the correct band selection (RF or VLC) for every D2D pair. Hence, we rely on DNNs due to their ability to extract complex models connecting the limited available information (in our case received powers and sum interferences) with the targeted output (selection of RF or VLC). Moreover, a trained DNN selects the band instantaneously in one step. Thus, this section describes the proposed DNN-based framework for band selection. Then, a

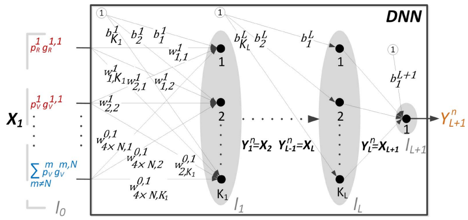


Fig. 2. Proposed DNN to select RF or VLC for a D2D pair.

low-complexity heuristic algorithm is designed to cope with the potential uncertainties in the DNN-based band selection in order to obtain a close-to-optimal performance.

A. DNN-Based Framework for Communication Band Selection

The band selection (RF/VLC) for every D2D pair from the N pairs can be seen as N identical binary classification problems. Thus, we design a DNN with $4 \times N$ input vector (denoted as $\mathbf{X_1}$) containing the received powers measured by every DUE_r from its related $\mathrm{DUE_t}$ and the sum interference imposed on every $\mathrm{DUE_r}$. Both these values are reported for VLC and RF, and the $\mathrm{DUE_r}$ reports its four measurements within one message. Then, based on $\mathbf{X_1}$, the DNN returns the proper band selection for the n-th D2D pair. Due to the nature of the defined RF/VLC band selection problem based on the received powers and sum interferences, the DNN is required to have a fully-connected architecture without neither features' extraction nor feed-back connections. Hence, the DNN is composed of an input layer (i.e., l_0), represented by $\mathbf{X_1}$, L sequential hidden layers (i.e., $\{l_1, l_2, \ldots, l_L\}$), and an output layer (i.e., l_{L+1}), see Fig. 2. The elements of $\mathbf{X_1}$ are fed to l_1 and, then, the output vector of each layer is the input vector of the following layer. Every hidden layer l_j (where $j \in \{1, \epsilon, L\}$) is composed of K_j neurons and the output layer l_{L+1} is composed of a single neuron for binary classification. Every layer l_j, except the input layer, inserts each input element *i* from its input vector $\mathbf{X_j}$ to every neuron *u* in this layer with a corresponding weight $w^j_{i,u}$. Every neuron in the layer l_j: i) performs the dot product between the input vector $\mathbf{X_j}$ and the corresponding weights, ii) adds the corresponding bias b^j_u, and iii) inserts the resulting value to a sigmoid activation function. Hence, the output of the layer l_j (i.e., any hidden layer or the output layer l_{L+1}) is:

$$\mathbf{Y^n_j} = sigmoid(\mathbf{W^j}.\mathbf{X_j} + \mathbf{b^j}) \tag{7}$$

where $sigmoid(.)$ is the sigmoid function $sigmoid(A) = \frac{1}{1+exp(-A)}$ which returns output values between zero and one, $\mathbf{W^j}$ contains all weights of the links between the inputs of l_j (i.e., $\mathbf{X_j}$) and all $\mathbf{K_j}$ neurons in l_j, and $\mathbf{b^j}$ includes the biases of all $\mathbf{K_j}$ neurons in l_j. The output of any hidden layer $\mathbf{Y^n_j} = \mathbf{X_{j+1}}$ for $j \in \{1, \epsilon, L\}$ is of a length K_j. Similarly, as the output layer l_{L+1} contains one neuron (i.e., $K_{L+1} = 1$), the output of l_{L+1} (i.e., Y^n_{L+1}) is a single value that represents the probability that the n-th D2D pair should select the RF band. Hence, the DNN's output represents the band selection as:

$$z^n_{DNN} = \begin{cases} 1 & \text{if } Y^n_{L+1} > 0.5 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

To train the DNN, a set of "training samples" is collected. Each training sample contains the measured received powers and sum interferences from every $\mathrm{DUE_r}$ in both RF and VLC (i.e., $\mathbf{X_1}$), accompanied with a targeted output, which is the optimal selection of RF or VLC for the n-th D2D pair derived by the exhaustive search (z^{n*}). The collected samples are fed to the DNN with random weights and biases. Then, the difference between the predicted and targeted band selection is evaluated via binary cross-entropy loss function defined as:

$$\delta = -[\![z^{n*} == 1]\!] log\left(Y^n_{L+1}\right) - [\![z^{n*} == 0]\!] log\left(1 - Y^n_{L+1}\right) \tag{9}$$

Using scaled-conjugate gradient back-propagation [16], the weights and the biases in the DNN are continuously and iteratively updated to minimize the average loss function over the training samples. The training of the DNN continues until the maximal number of iterations is reached or the prediction accuracy improvement becomes negligible.

Note that collecting the training samples and training the proposed DNN is executed offline, e.g., by simulations. Then, in the real mobile network, the previously trained DNN is used to instantly determine the most suitable band (RF or VLC) for every D2D pair simultaneously. In order to select RF or VLC for all D2D pairs, the elements of the DNN's input vector $\mathbf{X_1}$ are resorted for each pair in line with the way the DNN is trained. For instance, let us say that the DNN is trained to predict the band selection for the first D2D pair (the pair for which the received powers and the sum interferences in RF and VLC are put at the beginning of $\mathbf{X_1}$). Then, to predict the band selection for the second D2D pair, we put the received powers and the sum interference powers (in RF and VLC) measured at the $\mathrm{DUE_r}$ of the second pair at the beginning of $\mathbf{X_1}$. Hence, the same DNN is copied N times and the inputs are inserted to each of the N DNNs in a different order to extract the band selection of all N D2D pairs simultaneously and in parallel within a single step (i.e., not sequentially).

B. Proposed Heuristic Algorithm for DNN's Output Adjustment

The received sum interferences in the DNN's inputs do not always explicitly express the mutual relations among the D2D pairs. Thus, potential uncertainties in the DNN's decision can appear and a gap can exist between the reachable statistical prediction accuracy when only the received powers and sum interferences are known and the accuracy if all channel gains would be perfectly known. This gap in the prediction accuracy can impact negatively on the communication quality due to the fact that our problem is a binary decision problem and any misclassification (incorrect decision at the DNN's output) can lead to an increase in the interference. Thus, we propose a very low-complexity heuristic approach that deals with the impact of the DNN uncertainties and minimizes the gap in the prediction accuracy of the DNN. The proposed heuristic algorithm builds on the probabilities of RF and VLC resulting from the DNN and corrects the potential misclassifications in order to improve the performance of the band selection and to reach a communication quality that is closer to the optimum. The DNN's output Y^n_{L+1} represents the probability of the n-th pair using RF. Thus, the closer the output is to 0.5, the higher the uncertainty about the band selection is.

Algorithm 1 The Proposed Band Selection Scheme

1: **for all** $n \in \{1, \dots, N\}$ (processed in parallel) **do**
2: derive Y_{L+1}^n via DNN
3: determine z_{DNN}^n based on (8)
4: set $z_{I-DNN}^n = z_{DNN}^n$ (Initial band selection)
5: **if** $Y_{L+1}^n \in [0.5-\alpha, 0.5+\alpha]$ **then** $S_{uc} = S_{uc} \cup \{n\}$
6: determine initial ϕ and *EE*
7: sort all pairs in S_{uc} in ascending order acc. to $|Y_{L+1}^n - 0.5|$
8: **for** $n \in S_{uc}$ (sequentially acc. to the sorting in line 7) **do**
9: $z_{I-DNN}^n = 1 - z_{I-DNN}^n$ (switch band of *n*-th pair)
10: determine new ϕ and *EE*
11: **if** new $\phi <$ old ϕ **then**
12: keep z_{I-DNN}^n (keep new band)
13: **else**
14: **if** new *EE* > old *EE* & new $\phi =$ old ϕ **then**
15: keep z_{I-DNN}^n (keep new band)
16: **else**
17: $z_{I-DNN}^n = 1 - z_{I-DNN}^n$ (retrieve initial band)

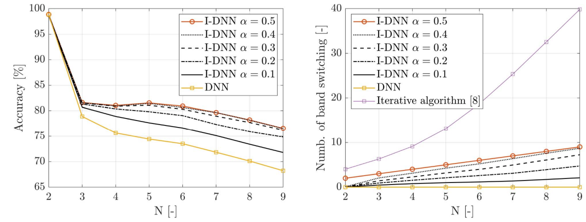
This uncertainty motivates us to improve the decisions for less confident situation(s). Thus, we introduce a parameter $\alpha \in \langle 0, 0.5 \rangle$ considering that the DNN is uncertain about the band selection if $Y_{L+1}^n \in [0.5-\alpha, 0.5+\alpha]$. Hence, the improved DNN's decision z_{I-DNN}^n is expressed as:

$$z_{I-DNN}^n \begin{cases} z_{DNN}^n & \text{if } Y_{L+1}^n < 0.5-\alpha \text{ or } Y_{L+1}^n > 0.5+\alpha \\ z_x^n & \text{if } 0.5-\alpha \le Y_{L+1}^n \le 0.5+\alpha \end{cases} \tag{10}$$

where z_x^n indicates the uncertainty in the band decision if the DNN's output for the *n*-th D2D pair is within an *uncertainty domain* $[0.5-\alpha, 0.5+\alpha]$ and the DNN's decision is revised. Based on this, we introduce a set S_{uc} that includes all D2D pairs from the uncertainty domain (S_{uc} includes $|S_{uc}| = N_{uc}$ pairs). The proposed heuristic algorithm (see Algorithm 1) starts after the DNN performs its decision (based on (8)) for all D2D pairs (lines 1, 2, and 3 in Algorithm 1). Then, the D2D pairs from S_{uc} are sorted according to $|Y_{L+1}^n - 0.5|$ in an ascending order (line 7). Following this ascending order, the D2D pair for which the DNN's decision is closest to 0.5 switches its communication band to VLC if this pair is assigned to use the RF band according to the DNN's decision and vice versa (line 9). If the outage ratio is decreased by the switching or if a higher average energy efficiency is reached without increasing the outage, the D2D pair remains in the new band (lines 12 and 15). Otherwise, the D2D pair switches back to its initial assigned band in line with the DNN's decision (line 17). This process is done sequentially for all other sorted D2D pairs in the uncertainty domain. After checking all pairs in the uncertainty domain, the algorithm is terminated. Considering N_{uc} D2D pairs in the uncertainty domain, the proposed algorithm checks the band switching N_{uc} times, where $N_{uc} \le N$ depends on α.

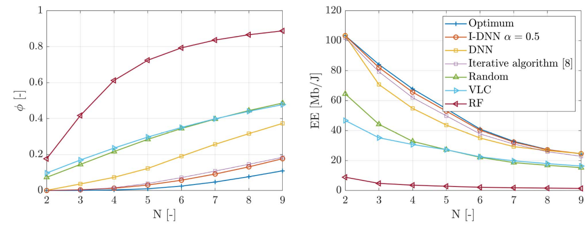
IV. PERFORMANCE ANALYSIS

For simulations, we assume a 30 × 30 m indoor area with two to nine D2D pairs deployed uniformly. As in [8], we assume that every two users are willing to communicate with



(a) Prediction accuracy (b) Numb. of band switching

Fig. 3. Statistical results for DNN efficiency evaluation vs *N*.



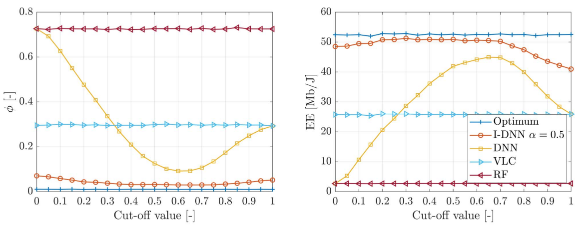
(a) Outage ratio (b) Energy efficiency

Fig. 4. Evaluation of communication quality vs *N*.

each other. Hence, within every pair, the angles of the transmitter and the receiver with respect to each other are generated with a zero-mean Gaussian distribution with a standard deviation of 30°. In RF and VLC, we set the transmission power to 100 mW and the channel bandwidth to 20 MHz. The VLC bandwidth is set as in [17], [18] taking into account that LED-based VLC commonly utilize commercial LEDs which have a modest bandwidth [19]. The channel models and noise are based on [20] for RF and [10] for VLC.

For the training, the DNN's architecture is set by trial and error approach and the used structure is composed of four hidden layers with 18, 15, 12, and 6 neurons, respectively. To this end, many DNN's architectures have been tested and we have chosen the most suitable one in terms of the achievable prediction accuracy as well as the training complexity. The total number of collected samples for training is 2×10^6. Some samples are omitted and not included in the training in order to keep an equal number of samples that correspond to each of the possible outputs (RF or VLC) to avoid the class imbalance problem [21]. The results are averaged out over 20,000 drops, each with new users' positions and angles.

Fig. 3(a) shows the prediction accuracy achieved by the proposed DNN both without (denoted as DNN) and with the proposed heuristic algorithm (denoted as I-DNN) for different values of α. The two cases of $\alpha = 0.5$ and $\alpha = 0$ represent the two extremes when either all or none of the D2D pairs are checked by the proposed heuristic algorithm. Thus, the latter case is equivalent to the DNN without the heuristic algorithm. Fig. 3(a) demonstrates that the prediction accuracy increases with α and the heuristic algorithm is able to add an additional 10% accuracy on top of the accuracy reached by the proposed DNN when $\alpha = 0.5$. Fig. 3(b) illustrates that the higher accuracy achieved by increasing α is at the cost of a higher complexity (i.e., more D2D pairs need to be checked as more of them are in the uncertainty domain). Still, even if $\alpha = 0.5$, the average number of band switching is significantly reduced (by up to 78%) comparing to the iterative algorithm in [8]. To analyze the outage and the energy efficiency, we compare



(a) Outage ratio (b) Energy efficiency

Fig. 5. Evaluation of communication quality vs cut-off value.

the proposed solution with: 1) the optimal RF/VLC combination derived by the exhaustive search (denoted as Optimum), 2) a random band selection (Random), 3) RF only, where all pairs use RF, 4) VLC only, where all pairs use VLC, and 5) the iterative algorithm from [8], which reaches a close-to-optimal performance but requires the knowledge of all channel gains between all DUEs and results in a higher complexity (see Fig. 3(b)).

As shown in Fig. 4(a), the outage ratio increases with the number of D2D pairs for all algorithms due to the increasing interference. Disregarding whether the proposed heuristic algorithm is employed or not, the proposal outperforms all competitive algorithms. Fig. 4(a) further demonstrates that the I-DNN improves the DNN and reaches a close-to-optimal performance. The outage of the I-DNN is higher compared to the Optimum by only up to 6%, and lower than RF only, VLC only, and Random by up to 71%, 41%, and 40%, respectively.

The average energy efficiency (Fig. 4(b)) decreases with the increasing number of D2D pairs due to the increasing interference in both bands. Fig. 4(b) shows that the I-DNN increases the energy efficiency by up to 18, 2.2, and 2 times compared to RF only, VLC only, and Random, respectively. The I-DNN also outperforms the DNN by up to 22% and reaches almost optimal performance for all numbers of pairs.

We study also the effect of the DNN's cut-off value, i.e., the threshold value that represents the edge between the selection of RF or VLC based on the DNN's output Y_{L+1}^{n}. Note that the cut-off value is set to 0.5 in (8) and in the previous figures. Fig. 5 presents the outage ratio (Fig. 5(a)) and the average energy efficiency (Fig. 5(b)) versus the cut-off value. Fig. 5 shows that increasing the cut-off value improves the performance of DNN as the VLC usage ratio is higher than RF usage ratio. Thus, a higher cut-off value increases the accuracy of VLC selection more significantly than the inaccuracy of RF selection. Hence, the total prediction accuracy increases. Fig. 5 also demonstrates that with a cut-off value of 0.7, the DNN reaches the highest performance, but the I-DNN still reduces the outage by 70% (from 0.1 to 0.03) and achieves 12% gain in the energy efficiency comparing to the DNN. However, the I-DNN achieves the same outage and energy efficiency for all cut-off values between 0.4 and 0.7.

V. Conclusion

This letter has presented a DNN-based framework to select RF or VLC for D2D pairs to maximize the energy efficiency while minimizing the outage. A DNN is designed to give an initial band selection decision. Then, a low-complexity heuristic algorithm that copes with the possible uncertainties in the DNN's band selection decisions is proposed. The proposed solution is of a very low complexity and reaches a close-to-optimal performance and overcomes the existing works in terms of outage and energy efficiency.

The future research direction should aim at a distributed solution, where the bands are selected by the users based only on their local information without sharing any information centrally.

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