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Research Article

Machine Learning-Aided Energy Efficiency Strategy for Multiuser Cooperative Networks

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Cooperative communication is widely seen as a promising key technology for improving the energy efficiency of battery-driven multiple mobile terminals (MTs). In this study, we investigate the use of machine learning (ML) in multiuser cooperative access networks. Because MT cooperation and bandwidth allocation are considered two main issues in such networks, we design an ML-aided method to solve the bandwidth issues so that the proposed method can maximize the network's energy efficiency. Specifically, we use machine learning with artificial neural network (ANN) trained at base station (BS) (a) to decide whether MTs in the heterogeneous access network should cooperatively communicate and (b) to determine the optimal bandwidth allocation for this communication by distributing the trained ANN to all MTs. The computer simulation results show that under the described communication environment in this paper, the proposed method can provide 99.8% correct prediction for MT cooperation and output the optimal bandwidth allocation with at least 88% accuracy, which demonstrates the effectiveness of the proposed method. Besides, the simulations also show that the proposed method can provide about 14%–25% power consumption reduction, which validates the EE performance of the proposed method.

1. Introduction

In recent years, as mobile terminal (MT) applications are growing dramatically, the traffic loading on networks and the power consumption of each MT become very important issues in modern wireless networks. For reducing traffic loading and saving the power consumption for each MT, forwarding transmission via MTs using cooperative wireless methods, which are also called user cooperation, is widely considered a promising approach [1]. Recently, lots of studies have investigated power consumption of user cooperation in cellular systems [2–4]. For example, in [2], the authors studied MT cooperation-based traffic downloading for distributing content to MTs. In [3], the authors proposed a method to increase the energy efficiency (EE) of two-MT cooperative cognitive wireless networks with network coding. In [4], the tradeoff between throughput and energy consumption in cooperative cognitive radio networks was theoretically analyzed.

Due to the limited transmission power of battery-driven MTs, an appropriate access scheme for improving EE performance is necessary in uplink cellular systems. Besides, such low energy consumption scheme will offer the opportunity to accommodate more battery-driven MTs because the total energy consumption of the whole cooperative system can be reduced. In our previous work [5], we investigated user cooperation traffic loading and proposed a method for optimizing the bandwidth allocation strategy to save power in MTs. Theoretical analysis and experiments of evaluating the proposed method in [5] show that up to 70% of single MT's power can be saved via the method. However, this user cooperation-aided forwarding approach selects a proxy terminal to meet the total communication demands of other MTs, and thus, the proxy terminal (i.e., one of the MTs) tends to be allocated more bandwidth (or spectrum resources) and may suffer from frequency selective fading. As a result, the transmission performance of the proxy terminal is occasionally worse than expected.

Although the method in [5] can substantially improve performance, the decision on whether MTs should cooperate for transmissions and the optimal allocation of bandwidth for these cooperative transmissions still remain as essential problems in cooperative transmission systems. According to the analysis results for the bandwidth allocation proportion (called ν in [5]) which is used for deciding the bandwidth allocated for cooperative communication, there exists an optimal proportion value called ν_{op} that can minimize system power consumption in the considered cooperative heterogeneous access networks. To determine this optimal value ν_{op}, the base station (BS) needs to collect the channel state information (CSI) and traffic demand of each MT and perform a series of tasks, which causes delay and thus reduces communication efficiency such as throughput. Past experience and available data can be used to perform such tasks, which are complex and computationally expensive, but traditional approaches based on explicit rules and instructions are not necessary. In particular, the best power-saving performance can be obtained by cooperative communication among MTs with an exhaustive search for the optimal bandwidth allocation, while it costs a lot of computation. If the bandwidth allocation can be determined in a less costly way, the method in [5] would be more feasible.

Owing to the rapid growth of machine learning (ML), many difficult research issues have been solved by ML-based methods, especially in future communication systems [6]. Thus, various ML-based approaches for wireless communication have been proposed in recent years [7–23]. For example, in [8], the authors used an ML-aided method to predict trajectory and detect conflict for aerial vehicles. In [9], the authors proposed an ML-based method to solve the resource allocation problem in cognitive radio systems. In [11], an ML-based method was used to solve the iterative decoding issue for ultra-dense small cell networks with cooperative transmission. In [16], the authors proposed an ML-based method to process transmission antenna selection task in multiple-input-multiple-output (MIMO) systems. ML-based methods also have a potential to further improve energy efficiency in cooperative heterogeneous networks. Meanwhile, it is important to prioritize the key performance indices (KPIs) that include intelligence, connectivity, spectrum efficiency, and energy efficiency as described in [24] because considering all the KPIs consumes a lot of computational resources to construct an optimal solution for a wireless system. In summary, in recent years, various ML-based methods were proposed to solve difficult problems in wireless communications. However, for the EE optimization problem in cooperative heterogeneous networks in the next-generation communications, we still need intelligent solutions, which motivate our work in this paper.

From the literature about EE problem, it can be known that how to achieve optimal EE performance in cooperative system is a difficult optimization problem of resource allocation so that optimal solution may not be found with limited computing resources. However, with the aid of ML technologies, it becomes less complicated and more feasible. Therefore in this study, we propose an effective bandwidth allocation strategy with ML-based methods using artificial neural networks (ANNs) for user-cooperative traffic forwarding. In our previous study [5], by averaging the effects of small-scale fading, each MT uploads its position and traffic demand to the BS. The BS then uses conventional methods to determine if cooperative communication would be more efficient and calculate ν_{op} with the help of this uploaded information. The results, noncooperative or cooperative communication (i.e., the communication mode) along with the value of ν_{op}, are returned to each MT and the BS performs follow-up operations. In ML-based approaches, the BS can further utilize the forementioned information to train or update ANNs, which are then used to predict the best communication mode and the value of ν_{op} without the existing algorithms. Once ANNs have been trained on the BS side, the trained ANN can be distributed to each MT by operator updates. Then, the MTs can use these trained or updated networks to determine whether they should use cooperative transmissions and further predict the value of ν_{op} (within an allowed error, of course) for the cooperative communication case. Finally, it is not necessary to upload the MT's information to the BS, and this reduces the system complexity and improves EE. It should be noted that, to apply it in a realistic transmission environment, here, we consider a generalized channel attenuation model with frequency selective fading and spatially correlated shadowing, in which the effect of small-scale fading is averaged for focusing on averaged transmission quality.

The main contributions of this paper are as follows:

(i) We introduce an ML-aided method in cooperative communications based on the validated evaluation results in [5], in which an effective energy efficiency optimization method is provided

(ii) The proposed ML-aided method predicts transmission performance parameters such as the optimal bandwidth proportion coefficient ν_{op} by using MT deployments and their communication demands. Henceforth, the proposed ML-aided methods can improve the computational cost and EE

(iii) A more realistic environment with the frequency selective fading channel and effect of spatially correlated shadowing is applied to the evaluation in this paper. To the best of our knowledge, there has been no previous work which dealt with the issue of bandwidth allocation under frequency selective channel in cooperative communications, although this issue is very important and may affect the system performance substantially

The rest of this paper is organized as follows. Section 2 describes the system model and formulates the problem in this study. Section 3 introduces the proposed method.

Section 4 provides simulation results. Finally, Section 5 concludes our work.

2. System Model and Problem Formulation

In this study, we consider an existing heterogeneous network that includes a set of MTs denoted as $\mathcal{U} = \{1, \cdots, U\}$ and indexed with $u = 1, \cdots, U$ together with a BS deployed in the network. The noncooperative and cooperative transmission scenarios considered in this study are illustrated in Figure 1. The MTs are in close proximity to each other and are able to communicate with the BS. Each MT is equipped with single antenna whereas the BS is equipped with M centralized antennas. The communications among the BS and MTs utilize an allocated bandwidth resource B for the uplink data transmissions. To make the proxy receive the traffic from other MTs and transmit the total traffic to the BS simultaneously, each MT is with two types of transmission modules: one can be operated as cellular link for sending data to the BS, and the other one can perform device-to-device (D2D) link for local data exchange with other MTs. In this type of network, all of the MTs are uniformly distributed in a circular communication area of radius R_{coop} that is R_{cell} away from the BS. Here, the radius of the cooperative-communication area depends on the capability of the D2D link.

In the conventional noncooperative transmission scenario, each MT directly sends its communication demand $C(u)$ to the BS using the equally allocated nonoverlapping bandwidths B/U. In the cooperative transmission scenario [5], the available bandwidth is divided into two parts: νB and $(1 - \nu)B$. The MTs, which are also known as clients, equally occupy the partial nonoverlapping bandwidth resource of νB to communicate with a proxy using multiple D2D links. In other words, the allocated bandwidth for each MT is $\nu B/(U - 1)$. The corresponding bandwidth allocations is shown in Figure 2. The proxy, which is selected from the MT set $\mathcal{U}$, works as a data aggregator and sends the total traffic demands $C_{\text{all}} = \sum_{u=1}^{U} C(u)$ to the BS using the remaining bandwidth $(1 - \nu)B$.

Because ν is a coefficient indicating proportion in our bandwidth allocation strategy, it can range from 0 to 1. The analysis in our previous work [5] shows that the transmit power at the clients or proxy is mathematically infinity in the two extreme cases of $\nu = 0$ and $\nu = 1$ because one of the clients or proxy is allocated without any bandwidth. Therefore, there exists an optimal value ν_{op} that minimizes the power consumed by the whole system, and ν_{op} indirectly varies with respect to the MT deployments, the selected proxy, and the uplink CSI. This is the key finding in [5], and the existence of ν_{op} enables ML-based approaches to simplify the system and hence improves energy efficiency.

3. Proposed ML-Aided Methods for Cooperative Communications

In our previous study [5], we proposed an effective method for heterogeneous cooperative networks that can save up to

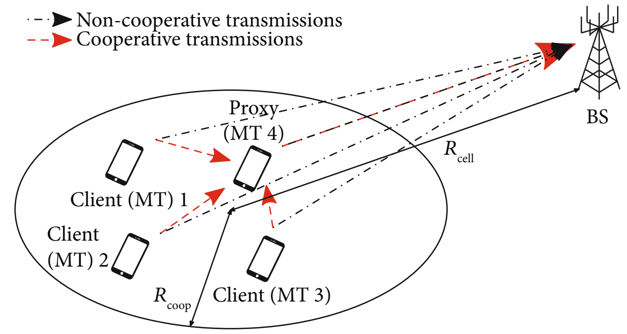

Figure 1: Noncooperative and cooperative transmissions with $U = 4$.

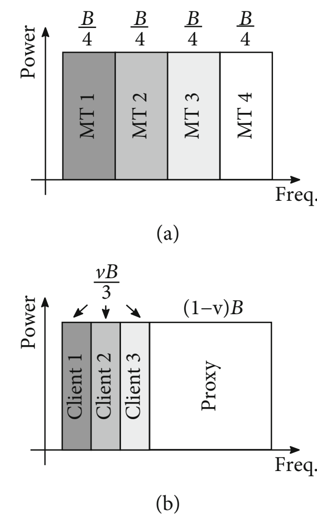

Figure 2: Bandwidth allocation strategy for the non-cooperative and cooperative transmissions with $U = 4$.

70% of MT transmit power. However, two major issues still remain in this method: One is how to decide if MTs should cooperate, and the other one is the proportion of bandwidth allocation to each MT. Therefore, in this study, for a given MT deployment and their communication demands, our goal is to use ML methods to resolve the following two issues: (a) deciding cooperative or noncooperative communication among MTs and (b) if cooperative, how the optimal value of ν_{op} is effectively determined. For this purpose, we first collect some data and generate a database $\mathcal{B}$ to train the ML algorithms. Database $\mathcal{B}$ consists of an input space $\mathcal{V}$ and two output spaces $\mathcal{T}_1$ and $\mathcal{T}_2$. The input–output pairs of $\mathcal{V}$ and $\mathcal{T}_1$ are used to train an ANN to determine the communication mode, and the input-output pair of $\mathcal{V}$ and $\mathcal{T}_2$ is used to train another ANN to predict the optimal value of ν_{op}. The generation of the database and the training of ANNs are performed in the offline phase, as shown in Figure 3.

In the input space $\mathcal{V}$, there are N possible feature vectors. Since large-scale fading is highly dependent on the geometrical locations and small-scale fading has been averaged, we consider each feature vector $\mathcal{V}(n), n = 1, \cdots, N$, which consists of MT deployments and their communication

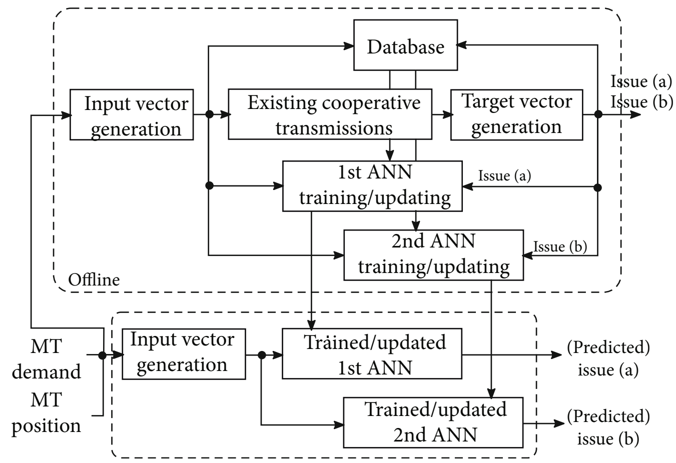

FIGURE 3: Functional block diagram of the proposed ML-aided bandwidth allocation strategy for the considered cooperative transmissions.

demands. The n-th feature vector for the input space $\mathscr{V}=\{\mathscr{V}(n)\}_{n=1}^{N}$ is written as

$$\mathscr{V}(n)=\left\{\{C(u,n),X(u,n),Y(u,n)\}_{u=1}^{U}\right\}^{T}, \tag{1}$$

where $X(u,n)$ and $Y(u,n)$ denote the n-th horizontal and vertical coordinates of MT u, respectively, and $C(u,n)$ is the communication demand of MT u at the n-th position. Certainly, in our future work, we can consider more parameters such as small-scale fading and mobility, to extend our study for more complicated scenarios.

Both output space $\mathscr{T}_1$ and $\mathscr{T}_2$ have N target values, and the n-th element in $\mathscr{T}_1=\{\mathscr{T}_1(n)\}_{n=1}^{N}$ and $\mathscr{T}_2=\{\mathscr{T}_2(n)\}_{n=1}^{N}$ is formulated as

$$\mathscr{T}_1(n)=\begin{cases}\{1,0\}^{\mathrm{T}}, & \text{for noncooperative communication,}\\ \{0,1\}^{\mathrm{T}}, & \text{for cooperative communication,}\end{cases} \tag{2}$$

$$\mathscr{T}_2(n)=\nu_{\mathrm{op}}(n), \tag{3}$$

where "1" and "0" in (2) represent the corresponding logical variables of "true" and "false," respectively. The values of $\mathscr{T}_1(n)$ and $\mathscr{T}_2(n)$ for all n are obtained from our previous study [5]. More specifically, for arbitrary n, we first exhaustively search for the optimal $\nu_{\mathrm{op}}(n)$ and record it in $\mathscr{T}_2$ and then further calculate the total consumed power with the corresponding $\nu_{\mathrm{op}}(n)$ for both communication modes (the calculations for noncooperative and cooperative $\nu_{\mathrm{op}}(n)$ follow equations (21) and (22) in [5]). In the last step, we compare the transmit power to determine the best communication mode and record the results in $\mathscr{T}_1$.

Once the database $\mathscr{B}$ is generated, two ANNs (i.e., models or functions) $\mathbb{M}_1^*$ and $\mathbb{M}_2^*$ are trained by substituting $\mathscr{V}$, $\mathscr{T}_1$, and $\mathscr{T}_2$ into the given network structures and training them. Generally, $\mathbb{M}_1^*$ and $\mathbb{M}_2^*$ can be written as

$$\mathbb{M}_i^*=\arg\min_{\mathbb{M}_i}\mathscr{L}_i(\mathscr{T}_i,\mathbb{M}_i(\mathscr{V})), \tag{4}$$

where $i=1$ and $i=2$ denote the first and second ANNs, respectively, and $\mathscr{L}_i$ is the loss function used for network training. After both ANNs have been trained, $\mathbb{M}_1^*$ and $\mathbb{M}_2^*$ can be used to predict the answers to communication mode determination and bandwidth allocation. Here, this process is called "Online Phase," which is also shown in Figure 3 with gray frames. Note that the "Existing Cooperative Transmissions" block in Figure 3 can be realized with any existing cooperative transmission method such as the one provided in [5]. The proposed method is summarized in Algorithm 1.

4. Simulation Results

In the simulations, we collected N sets of data for training $\mathbb{M}_1^*$ and $\mathbb{M}_2^*$ and N_{pred} sets of data for testing these trained ANNs. To evaluate the accuracy of the proposed ML-based prediction methods, we defined a parameter $\rho(n')$, where $n'=1,\cdots,N_{\mathrm{pred}}$, to represent the predicted accuracy of the n'th ν_{op}. It is expressed as

$$\rho\left(n'\right)=1-\frac{\left|\tilde{\nu}_{\mathrm{op}}\left(n'\right)-\nu_{\mathrm{op}}\left(n'\right)\right|}{\nu_{\mathrm{op}}\left(n'\right)}, \tag{5}$$

where $\tilde{\nu}_{\mathrm{op}}(n')$ is the predicted optimal proportion of bandwidth for cooperative communication, which is mainly dominated by the MT deployments and communication demands. $\tilde{\nu}_{\mathrm{op}}(n')$ can be calculated by

$$\tilde{\nu}_{\mathrm{op}}\left(n'\right)=\mathbb{M}_2^*\left(\mathscr{V}\left(n'\right)\right). \tag{6}$$

Finally, the output of $\mathbb{M}_1^*(n')$ and the complementary cumulative distribution function (CCDF) of $\rho(n')$ for all of $n'=1,\cdots,N_{\mathrm{pred}}$ are used to evaluate the proposal.

The main simulation configurations and settings for the ANN training in this study are listed in Tables 1 and 2, respectively. Here, the parameters of ANN such as maximum number of epochs or number of layers are chosen by

Input: $C(u,n), X(u,n), Y(u,n), u = 1, \cdots, U, n = 1, \cdots, N$
Output: $\mathbb{M}_i^*, i = 1, 2$
Initialization: $\mathscr{V} = \varnothing, \mathscr{T}_1 = \varnothing, \mathscr{T}_2 = \varnothing$, Create ANNs $\mathbb{M}_i$ for $i = 1, 2$
%Generation of input space in database $\mathscr{B}$
for $n = 1, \cdots, N$ **do**
    $\mathscr{V}_{temp} = \varnothing$
    for $u = 1, \cdots, U$ **do**
        $\mathscr{V}_{temp} = \mathscr{V}_{temp} \bigcup C(u,n) \bigcup X(u,n) \bigcup Y(u,n);$
    end
    $\mathscr{V} = \mathscr{V} \bigcup \mathscr{V}_{temp}^T$
end
%Generation of output space in database $\mathscr{B}$
for $n = 1, \cdots, N$ **do**
    Calculate $v_{op}(n)$ by substituting $\mathscr{V}(n)$ and using exhaustive searching based on [5];
    $\mathscr{T}_2 = \mathscr{T}_2 \bigcup v_{op}(n);$
    Calculate the total power consumption of non- cooperative and cooperative communications according to [5];
    if Non-cooperative power ≤ Cooperative power **then**
        $\mathscr{T}_1 = \mathscr{T}_1 \bigcup \{1, 0\}^T;$
    else
        $\mathscr{T}_1 = \mathscr{T}_1 \bigcup \{0, 1\}^T$
    end
end
%Training all of ANNs
for each $i = 1, 2$ **do**
    $\mathbb{M}_i^* = \arg\ \min_{\mathbb{M}_i} \mathscr{L}_i(\mathscr{T}_i, \mathbb{M}_i(\mathscr{V}))$
end

Algorithm 1: The proposed ML-based energy efficiency method.

doing numbers of simulations and select the values which can result in good learning performance. Note that because the area of cooperative communication is not large, the shadowing loss variations can be viewed as completely correlated for all MTs. Furthermore, according to [5, 26], a frequency selective channel model with L (indexed with $l = 1, \cdots, L$) subchannels (or paths) is adopted, and a intertap correlation coefficient matrix Θ_{ISI} for simulation of intersymbol interference (ISI) is also considered. The detailed parameters can be found in our previous study in [5]. With the consideration of current computational complexity and computer resources, we adopt one hidden layer with 10 nodes for the ANNs.

Table 3 shows the prediction results of the 1st ANN for communication mode. As indicated in the first row, there are 921 cases that should use cooperative communication and were correctly predicted (true positive cases), whereas there is no case that should be non-cooperative but was falsely predicted to be cooperative (false positive cases). Therefore, in the cases that cooperative communication was predicted, the correct rate is 100%. Similarly, as indicated in the second row, there are 77 cases that should use noncooperative communication and were correctly predicted (true negative cases), whereas there are 2 cases that should use cooperative communication but were falsely predicted to be noncooperative (false negative cases). Therefore, in the cases that noncooperative communication was predicted, the correct rate is 97.5%. In summary, among all 1,000 test cases, 998 cases were correctly predicted and 2 cases were incorrectly predicted. Therefore, the first ANN

Table 1: Main configurations.

Parameter	Value
Number of BS antennas, M	8
Number of MTs, U	4
Position of BS	(0, 0)
BS antenna deployment	Centralized
Distance between BS and center of communication area, R_{cell}	$\leq 10^3$ m
Radius of communication area, R_{coop}	20 m
MT deployment in communication area	Uniform
Proxy selection	Best channel condition
Bandwidth, B	20 MHz
Channel model	Frequency selective
Path loss exponent	-4
Shadowing correlation	Completely correlated
Shadowing standard deviation [25]	9.6
Fading model	Rayleigh
Number of subchannels, L	4
Intertap correlation coefficient matrix for ISI	$\Theta_{\text{ISI}} = 0.95^{\lvert l-l' \rvert}/L$
Number of data for training, N	10^4
Number of data for testing, N_{pred}	10^3

Table 2: Parameters for the ANN training.

Parameters	Values
Number of hidden layers	1
Number of hidden layer nodes	10
Maximum number of epochs	10^3
Activation functions	Sigmoid
Validation data percentage	15%
Loss function for the 1st ANN	Cross entropy
Loss function for the 2nd ANN	MSE
Training algorithm for the 1st ANN	Scaled conjugate gradient
Training algorithm for the 2nd ANN	Levenberg–Marquardt

Table 3: Prediction results of 1st ANN.

Prediction result	Correct	Incorrect	Correct rate
Cooperative	921	0	100%
Noncooperative	77	2	97.5%
Total	998	2	99.8%

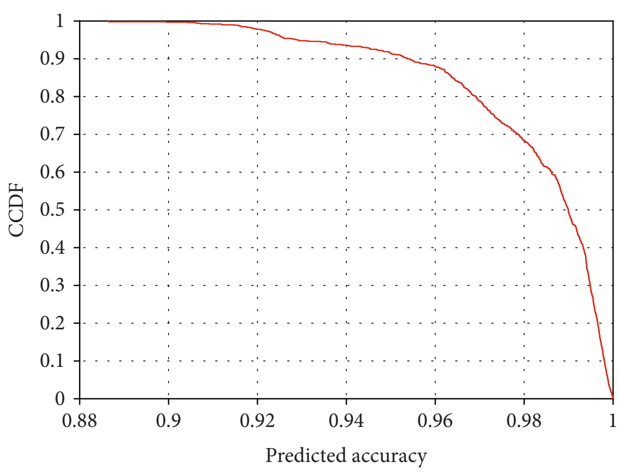

Figure 4: CCDF of the prediction accuracy of the second trained ANN $\mathbb{M}_2^*$.

of the proposed method predicted the communication mode with an accuracy of 99.8%.

Figure 4 shows the CCDF of the predicted accuracy for the second trained ANN $\mathbb{M}_2^*$. It can be seen that about 50% cases reach 99% prediction accuracy. Moreover, all the cases reach at least 88% prediction accuracy, which indicates the optimality of the output ν_{op} and means that bandwidth allocation is effectively optimized by the second ANN of the proposed method shown in Figure 3. This fact further verifies that when system is working with the proposed method, approximately 70% power consumption can be saved via cooperative communications as the experiment results in [5]. Consequently, from the results in Table 3 and Figure 4, it is obvious that the communication mode decision and bandwidth allocation mentioned in Section 3 can be effectively and accurately performed via the proposed

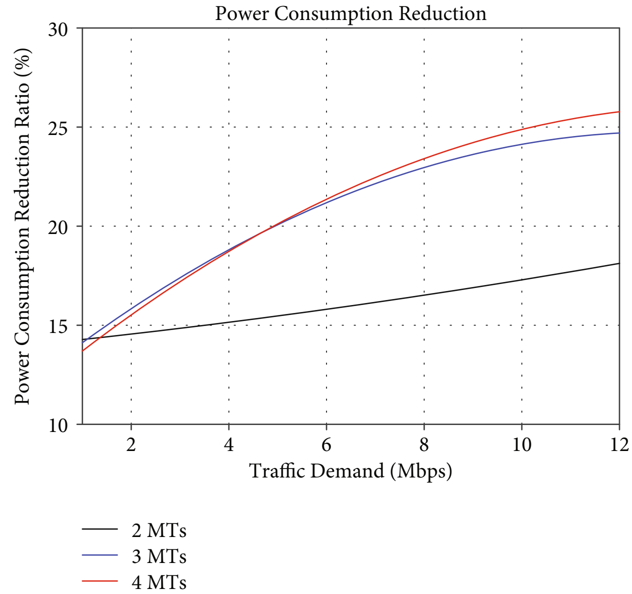

Figure 5: Power consumption reduction performance.

ML-based method with two ANNs. Specifically, after the training process of the two ANNs is finished, the first ANN can accurately predict whether the system should cooperate or not, and the second ANN can provide the optimal ν_{op} for optimizing EE performance, which makes the whole system always utilize energy in an optimal way.

Besides, since optimal bandwidth proportion $\tilde{\nu}_{op}(n')$ for cooperative communication can be predicted to reach optimal EE by using the proposed ML-aided method, here, we conduct simulations of cooperative communication with multiple MTs to validate the EE performance of the proposed method.

In the simulations, we evaluate the total power consumption of all MTs with and without proposed cooperative scheme under different traffic demands and check how much power consumption reduction can be obtained by using the proposed method. The simulation results are shown in Figure 5. The results shown here include the power consumption reduction results between systems using noncooperative and proposed cooperative communication schemes with 2 MTs, 3 MTs, and 4 MTs. From the results, it can be observed that, although the power consumption reduction performance is only about 14%–16% for system with small number of MTs, i.e., 2 MTs, for all traffic demands, it becomes much better which reaches maximally about 25% when MT number and traffic demand are getting larger. Besides the trend that larger MT number and traffic demand can result in better EE performance, there are also some points needed to be noted. Firstly, because of the physical constraints applied on the proxy, for example, maximum transmit power, we cannot increase the total communication demand without any limitation. Secondly, the results in Figure 5 are evaluated with consideration of the worst channel attenuation case. In other words, all MTs are affected by the shadowing, and hence, the large-scale fading is approximately identical. In real cases, however, shadowing on each MT may be quite different because of the surrounding obstacles. As a result, the benefits of user cooperation aided transmission forwarding can be further improved. Therefore, from these simulation results, it can be known that the proposed method can effectively reduce system power consumption in cooperative communications with large number of MTs.

In summary, the method proposed in this study provides an effective way to optimize the EE performance using the approach in [5], which showed that the proposed cooperative communication scheme can offer optimal EE performance with optimal bandwidth allocation ν_{op}. However, in [5] the optimal ν_{op} was found by exhaustive search, which is very computationally consuming and difficult to be implemented. With the ML-based approach proposed in this study, the optimal ν_{op} can be determined effectively and the cooperative communication scheme becomes much more feasible. Moreover, in practical applications, because the ML training can be performed offline, the system can work online after ML training with very limited computational resources. In addition, although some suboptimization algorithms in [27] can also be used to find ν_{op} with reduced complexity, they need large amount of feedback information from MTs to obtain high search performance. Comparing to these traditional suboptimization methods, some feedback information such as CSI could be reduced by using the proposed ML-based approach, which can also improve communication efficiency such as throughput.

Besides, here, we also provide simulation results of power consumption reduction by using proposed cooperative scheme. From the results, it can be observed that maximally 25% power consumption reduction can be obtained for larger number of MTs. Instead of the best case of 25% reduction, it can be seen that the proposed can provide at least about 14% power consumption reduction, which validates the EE performance of the proposed method.

5. Conclusion

In this study, we investigated the cooperative transmission strategy of MTs in heterogeneous network and proposed an ML-aided method to determine MT communication mode and bandwidth allocation. For the networks considered in this study, there are two essential issues: (a) whether the MTs should perform cooperative or noncooperative communication and (b) how the optimal bandwidth allocation is determined. To solve these problems, we adopted two ANNs to predict the correct answers. The simulation results show that the first ANN of the proposed method predicted the communication mode with an accuracy of 99.8% and the second ANN can output bandwidth allocation parameter ν_{op} with at least 88% accuracy, which demonstrates the effectiveness of the proposed method. Besides, we also provide simulation results of power consumption reduction by using the proposed cooperative scheme. The results show that 14%–25% can be obtained, which verifies the EE performance of the proposed method. Certainly, in practice, the effectiveness of the proposed ML-aided method needs to be further verified with consideration of small-scale fading based channel variation, and discussion about computational cost for the proposed ML-aided method is also necessary, which are left as our future works.

Data Availability

The data including simulation configurations, parameters, and results used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgments

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