Radio Resource Allocation in 5G New Radio: A Neural Networks Approach

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Abstract

The minimum frequency-time unit that can be allocated to a User Equipment (UE) in the fifth generation (5G) cellular networks is a Resource Block (RB). An RB is a channel composed of a set of OFDM subcarriers for a time slot duration. 5G New Radio (NR) permits a large number of block shapes varying from 15 kHz to 480 kHz. In this paper, we tackle the problem of RBs allocation to UEs. The RBs are allocated at the beginning of each time slot based on the channel state of each UE. The problem is formulated based on the Generalized Proportional Fair (GPF) formulation. We model the problem as a 2-Dimensions Hopfield Neural Networks (2D-HNN). Then, the energy function of 2D-HNN is investigated to solve the problem. Simulation results show efficiency of the proposed approach.

1. Introduction

The fifth generation (5G) New Radio (NR) supports multiple numerologies (*i.e.,* waveform configuration like subframe spacing) and Resource Blocks (RBs) get different shapes depending on the type of numerology. A RB is defined as a group of OFDM subcarriers for time slot duration [1]. In a downlink 5G system, a RB is the smallest frequency-time unit that can be assigned to a User Equipment (UE). The Base station (BS) assigns the RBs to UEs as a function of the channel qualities, and traffic demands.

A lot of resource allocation mechanisms have been introduced in literature. Authors in [2] introduce an optimization framework to maximize the energy efficiency of the downlink transmission of cellular OFDMA networks while considering discrete power and RBs allocation. The discrete power and discrete RBs are modeled by a single binary variable and a two stage close-to-optimal semidefinite relaxation (SDR)-based algorithm with Gaussian randomization is proposed to solve the formulated optimization problem. In this paper, we tackle the problem of RBs allocation to UEs. We model the RBs allocation problem as a 2-Dimension Hopfield Neural Network (2D HNN). The optimization problem is formulated based on the Generalized Proportional Fair (GPF) formulation and then rewritten in the form of the energy function of 2D HNN. The decreasing property of HNN energy function is investigated to solve the problem. The main motivation to use the 2D HNNs is that it can give an on-line solution due to its ability to process in parallel and thus it can save the computation time.

The remaining of this paper is organized as follows: section 2 introduces the system model and problem formulation. Section 3 presents the proposed 2D HNN based approach. Section 4 introduces the performance evaluation. Finally, section 5 concludes the paper.

2. System Model and Problem Formulation

We consider the downlink transmissions of a BS with a set of UEs denoted by $\mathcal{U} = \{1, 2, ..., U\}$. The BS considers the system bandwidth, which is divided into a set of RBs denoted by $\mathcal{B} = \{1, 2, ..., B\}$. The time domain is divided into equally spaced time slots with one millisecond time duration as that in the LTE systems.

The objective is to allocate the RBs to UEs such that the total data rate of all UEs is maximized while ensuring a certain level of fairness between them. The RBs are allocated to UEs at the slot boundary based on their channel states. Therefore, we use channel aware based Generalized Proportional Fair (GPF) scheduling that considers the multi-user diversity [3]. GPF based formulation gives different levels of trade-off between total data rate and fairness by using different values of the GPF parameter α. The data rate and user fairness trade-off optimization problem has to maximize the total data rate of all UEs while maintaining a certain level of long-term fairness. The maximum data rate of an UE u at time slot t can be approximated based on Shannon capacity model as follows [4, 5, 6]:

$$r_u(t) = \sum_{b\in\mathcal{B}} f_b x_{u,b}(t) \log_2(1 + \frac{p_u h_u(t)}{N_0 F}), \qquad (1)$$

where $x_{u,b}$ is the RB allocation result, with $x_{u,b} = 1$ means that RB b is allocated to UE u and $x_{u,b} = 0$ means the opposite case, f_b is the bandwidth of RB b, F is the total bandwidth, p_u is the transmission power of user u, h_u is the channel gain of user u, and N_0 denotes the noise power.

The average data rate of UE u up to time t can be defined as follows [7]:

$$\bar{R}_u(t) = \epsilon \bar{R}_u(t-1) + (1-\epsilon) r_u(t) \qquad (2)$$

where $\epsilon \in [0, 1]$. Therefore, the optimization problem can be formulated as follows:

$$\underset{x}{\text{maximize}} \quad \sum_{u\in\mathcal{U}} r_u(t)/[\bar{R}(t)]^\alpha \qquad (3a)$$

$$\text{subject to} \quad \sum_{b\in\mathcal{B}} x_{u,b} \le 1, \quad \forall u \in \mathcal{U} \qquad (3b)$$

$$x_{u,b} \in \{0, 1\}, \quad \forall u \in \mathcal{U}, b \in \mathcal{B} \qquad (3c)$$

The constraint (3b) is to ensure that each RB is allocated to one user only at the same time. The objective is to find the allocation matrix x that maximizes the total data rate of all UEs while ensuring a fair allocation.

3. Proposed 2D-Hopfield Neural Networks Based Approach

Artificial Neural Networks (ANNs) are a promising approach to solve optimization problems because it can save computational time due to the parallel processing and give an on-line solution. The ANNs consist of interconnected processing elements called neurons. These neurons work together to solve specific problems. According to its structure, the ANNs are classified into Feed-forward Networks and Feedback Networks or RNNs. Both types have to be configured, one way by training the neural network and letting its weights change according to learning rule. The other way is to set the weights explicitly by using a prior knowledge. HNNs, which are a type of RNNs, belong to the non-training model.

In HNNs, the output of each neuron is either '1' or '0' depending on the neuron input (*i.e.,* smaller or larger than its threshold). Every pair of neurons, neuron ij and neuron kl, are connected with the weight w_{ijkl}. In HNNs, The self connections of neurons are set to zero (*i.e.,* $w_{ijij} = 0$) and the connections between any two neurons are symmetric (*i.e.,* $w_{ijkl} = w_{klij}$). The updating rule of 2D Hopfield Neural Network is given by:

$$v_{ij}(t+1) = \begin{cases} 1, & \text{if } \sum_k \sum_l w_{ijkl} v_{ij}(t) \geq \theta_{ij} \\ 0, & \text{Otherwise} \end{cases} \tag{4}$$

where $v_{ij}(t)$ is the state of neuron (i, j), w_{ijkl} is the connection weight between neuron (i, j) and neuron (k, l), and θ_{ij} is the threshold of neuron (i, j).

HNNs have a value associated with each state of the network called the energy of the network $E(v)$:

$$E(v) = \frac{-1}{2} \sum_i \sum_j \sum_k \sum_l w_{ijkl} v_{ij} v_{kl} + \sum_i \sum_j \theta_{ij} v_{ij} \tag{5}$$

The value of the energy function decreases when the neurons are updated randomly based on the updating rule and converges to stable state which is the local minimum of the energy function [8, 9]. In this paper, this minimization property is investigated by defining and expressing the objective function in terms of neuron states v_i. Then, the connection weights w_{ij} and thresholds θ_i can be calculated by comparing the energy function with the formulated objective function.

We model the problem of RBs allocation as a 2D HNN. Here, we consider that there are B neurons for each UE (*i.e.,* number of neurons of each UE equals to the total number of RBs). Therefore, we can express the state of RBs allocation (x) of each each UE by the firing pattern of the neural network (*i.e.,* Firing neuron (u, b) means that the RB b is assigned to the user u and thus $x_{ub} = 1$). Fig. 1 (a) shows the neural network firing pattern and Fig. 1 (b) shows the corresponding RBs allocation.

The objective function of the optimization problem (3) can be written in the same form of HNN energy function as follows:

$$\begin{aligned} f(x) &= -\sum_{u\in\mathcal{U}} r_u(t)/[\bar{R(t)}]^\alpha \\ &= -\sum_{u\in\mathcal{U}} \sum_{b\in\mathcal{B}} \frac{f_b x_{u,b}}{[\bar{R(t)}]^\alpha} \log_2(1+\beta \frac{p_u h_u(t)}{N_0 w_u}) \\ &= \sum_{u\in\mathcal{U}} \sum_{b\in\mathcal{B}} \sum_{i\in\mathcal{U}} \sum_{j\in\mathcal{B}} \frac{f_b x_{u,b} \delta_{ubij}}{[\bar{R(t)}]^\alpha} \log_2(1+\beta \frac{p_u h_u(t)}{N_0 w_u}) \end{aligned} \tag{6}$$

where δ_{ubij} is defined as follows:

$$\delta_{ubij} = \begin{cases} 1, & \text{if } u = i \text{ and } b = j \\ 0, & \text{Otherwise} \end{cases} \tag{7}$$

The connection weights and thresholds can be calculated by comparing $f(x)$ in the above equation with the energy function of 2D HNN $E(x)$ in equation (5) as follows:

$$w_{ubij} = \frac{f_b \delta_{ubij}}{[\bar{R(t)}]^\alpha} \log_2(1+\beta \frac{p_u h_u(t)}{N_0 w_u}) \tag{8}$$

$$\theta_{ub} = 0, \ \forall \ u \in \mathcal{U} \ and \ b \in \mathcal{B} \tag{9}$$

Each RB can be allocated to one user only at the same time, to satisfy that we modify the updating rule of 2D-HNN in equation (4) to become as follows:

$$x_{ub}(t+1) = \begin{cases} 1, & \text{when } y_{ub}(t+1) = \max[y_{1b}(t+1), \ldots, y_{Ub}(t+1)] \\ 0, & \text{Otherwise} \end{cases} \tag{10}$$

where

$$y_{ub}(t+1) = \sum_{k\in\mathcal{B}} \sum_{l\in\mathcal{U}} w_{ubkl} x_{kl}(t) - \theta_{ub} \tag{11}$$

4. Performance Evaluation

The performance of the proposed approach is evaluated in this section in terms of achieved data rate and fairness. Our system consists of 10 UEs with different channel states. We consider that 100 RBs are available at each time slot with different width. We evaluate the performance of the proposed approach with different values of the GPF parameter α. We calculate the long-term data rate of all UEs and the fairness among them with different values of α.

Fig. 2 shows the fairness of UEs with different values of α. Increasing the value of α leads to higher fairness among the UEs since the RBs allocation algorithm aims to maximizes the total data rate at each time slot while considering the average data rate of each user over the time. Therefore, the RBs allocation algorithm gives more resources to the users with bad channel conditions. However, setting the value of α to small values decreases the fairness. In

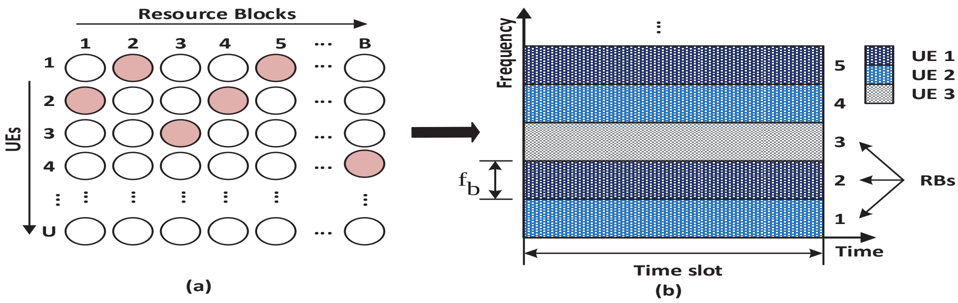

Figure 1: The relation between firing pattern of neural network and RBs allocation

this case, the RBs allocation algorithm aims to maximize the total data rate at each time slot without considering the average data rate of each user over the time and then the UEs with good channel conditions get more resources.

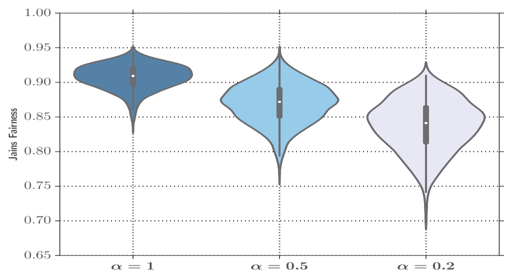

Figure 2: Fairness among UEs with different values of α

Fig. 3 shows the Empirical Cumulative Distribution Function (ECDF) of total data rate of all UEs with different values of α. As shown in this figure, decreasing the value of α leads to higher total data rate and vice versa. The importance of the average data rate of each user over the time increases when increasing the values of α and this gives higher probability to the UEs with bad channel conditions to get more resources causing decreasing in the total data rate. Consequently, the RBs allocation algorithm with low values of α allocates more resources to UEs with good channel conditions and this leads to increase the total data rate of all UEs.

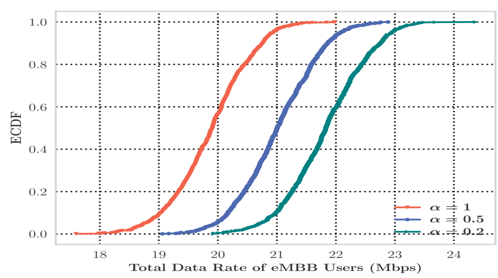

Figure 3: ECDF of the total data rate of all UEs (Mbps) with different values of α

5. Conclusion

In this paper, we have considered the problem of RBs allocation to UEs in 5G NR. The problem of RBs allocation is formulated based on the GPF. We modeled the problem as a 2D-HNN. Then, the minimization property of energy function of 2D-HNN is investigated to solve it. The results shown that the proposed algorithm gives a fair allocation of the RBs to UEs.

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