A Deep Learning Based Automatic Interference Avoidance Resource Allocation Scheme for SCMA Systems

Peng Yang\textsuperscript{a,1}, Wei Wang\textsuperscript{2}, Weimin Mao\textsuperscript{3}, Guoyi Zhang\textsuperscript{3}, Jie Cai\textsuperscript{1}, Danke Hong\textsuperscript{3}, Hailong Zhu\textsuperscript{3}, Jianhui Zhang\textsuperscript{1} and Shengli Chen\textsuperscript{1}

\textsuperscript{1}Guangzhou Branch, China Mobile Communications Group Guangdong Co.,Ltd
\textsuperscript{2}Guangzhou Power Supply Bureau, Guangdong Power Grid Co.,Ltd
\textsuperscript{3}China Southern Power Grid Co.,Ltd

*Corresponding author email: yangpengjk@chinamobile.com

Abstract. Sparse code multiple access (SCMA) is able to provide high spectral efficiency and massive connectivity, hence it is considered as a promising scheme for the fifth generation (5G) systems. This paper proposed a radio resource allocation scheme based on deep learning for SCMA systems, with the aim to automatically avoid the inter-cell interference. A long short term memory (LSTM) network is adopted to learn the past interference characteristics and predict the interference power in the current subframe. Radio resource blocks with less predicted interference power are then selected for users to transmit signals. Simulation results show that the proposed scheme outperforms the moving average prediction method and has significant gains over the random radio resource block allocation in terms of achievable bit error rate in SCMA systems.

Keywords: SCMA; 5G; automatic resource allocation; LSTM; interference avoidance;

1. Introduction
In the fifth generation (5G) systems, sparse code multiple access (SCMA) \[1\] is envisioned as a promising technique which is able to achieve high spectral efficiency and massive connectivity. SCMA allows multiple users to use different codewords in overlapped time and frequency resources for signal transmission. A message passing algorithm (MPA) \[2\][3][4] can be used at the receiver to remove the intra-cell interference between users for signal detection, which can approximate the performance of the maximum likelihood detection with reduced complexity. However, inter-cell interference remains the performance limiting factor for SCMA systems.

In order to ensure end to end performance of users, network slicing \[5\] is adopted, where in the 5G air interface, radio resources can be reserved for a certain users to achieve high reliability of transmission. However, users may still be interfered by co-channel interference originated from the neighboring cells.

Deep learning algorithms have been applied in 5G applications for radio resource allocation. Researchers \[6\] [13] [14] used reinforcement learning methods to address the resource allocation or resource management scenarios to achieve long term optimization effect on traffic control actions. In \[7\] Mennes used two algorithms based on neural network to predict free frequency slots in a Multiple Frequencies Time Division Multiple Access (MF-TDMA) network. In \[8\] Shi used deep neural network to minimize the weighted minimum mean square error (WMMSE) in algorithm addressing the resource allocation problem. Method \[9\] combining deep learning Kalman filter and fuzzy inference is applied in establishing a broadcasting scheme in a vehicular adhoc networks, where deep...
neural network is used to evaluate the accuracy level of cooperative awareness messages estimator for broadcasting. Besides deep learning algorithm based on convolution neural network, recurrent neural networks such as long short term memory (LSTM) network are commonly used in resource allocation researches in [10].

In this paper, we investigate the strategy of radio resources allocation to avoid inter-cell interference for users in SCMA systems. The interference power received at individual resource blocks is input into a LSTM network and is predicted before signal transmission. The resource blocks with less predicted interference are then selected for signal transmission. It is shown in the simulations that the proposed algorithm has high potentials to predict and avoid inter-cell interference and it is able to achieve better performance than traditional resource allocation schemes.

The rest of the paper is organized as follows. Section 2 describes the system model. Section 3 introduces the proposed resource allocation scheme. Simulation results are presented in Section 4. Finally conclusions are given in Section 5.

2. System Model
Consider a wireless system with $U$ users sharing $K$ resources to transmit signals to a base station (BS). It is assumed that $U$ users served by the system in an SCMA manner with $U > K$. The transmitted signal of user $u$ is grouped in every $\log M$ binary bits and is mapped to a predefined codeword $x_u$, which is selected from a codebook of user $u$. The codebook has a size of $M$. The codeword $x_u$ has $N$ non-zero elements ($N < K$) hence it is a sparse vector. Let $x_u = [x_{u1}, x_{u2}, \cdots, x_{uK}]^T$ denote the codeword used by user $u$ and $h_u = [h_{u1}, h_{u2}, \cdots, h_{uK}]^T$ denote the channel vector from user $u$ to the BS, the received signal $y$ at the BS can be obtained by

$$y = \sum_{u=1}^{U} \text{diag}(h_u)x_u + I + n$$

Where $y = [y_{u1}, y_{u2}, \cdots, y_{uK}]^T$ is the received signal vector, $I$ is the inter-cell interference encountered at the receiver and $n$ is white Gaussian noise vectors with zero mean and variance $\sigma^2$.

A factor graph can be used to represent the SCMA system as shown in Fig. 1, where UNs and RNs stand for the user nodes and the resource nodes, respectively. A UN is associated with the codebook of the user and an RN is associated with the resource element. A factor graph branch is connected between a UN and an RN if and only if a codebook has a non-zero element in the corresponding RN. In the system without inter-cell interference $I$, knowing the codebook of all the users and the channel coefficients between the users and the BS, the transmitted signal of all the users can be detected effectively using the MPA in an iterative manner [2][4].

![Figure 1. An SCMA system represented by a factor graph.](image)

In multi-cells scenarios, the RNs may be interfered by co-channel interference originated from the users in the neighbouring cells, i.e., $I$ in Eq. (1) can not be neglected. In this case, it is desirable that the RNs with less interference in the systems are selected for signal transmission. In the following, we propose a deep learning based scheme to predict and select the RNs with less interference for signal transmission.

3. Proposed Scheme
To address the interference pattern prediction problem, the LSTM architecture is used to predict the characteristics of the interference based on its history data. The LSTM network is one type of
recurrent neural networks, and has been frequently used in the domain of speech recognition because of its ability to store the long-term dependency of the input data. In this scheme the LSTM network is adopted, and the architecture of the deep learning network is illustrated in Fig. 2. The sequential network contains a sequence of four layers: a regression output layer, a fully connected layer, a LSTM layer and an input layer.

![LSTM Network Architecture](image)

**Figure 2.** A simple regressive LSTM network architecture.

Note that the input data fed into the input layer of LSTM should be sequential data with time-dependency. Simulation indicates the convergence of this model and its ability to predict the resource allocation. Fig. 3 illustrates the training progress of this model.

![RMSE and Loss vs. Iterations](image)

**Figure 3.** RMSE and Loss vs. iteration numbers when training the LSTM network.

### 4. Simulation Results
Simulations of the proposed scheme are conducted to evaluate its performance. It is assumed that in an SCMA system 6 users share 4 RNs (U = 6, K = 4, M = 4) to communicate with the BS. It is further assumed that 6 RNs are available which are 5MHz apart from each other. The radio resource allocation strategy is to select 4 RNs out of 6 RNs before each signal transmission. For simplicity, only a single antenna is assumed at both the user and at the BS. The transmitted signals of all users are disturbed by both the AWGN and interference originated from the users of the neighbouring cells. In the simulation, the interferes are assumed to be independently 4QAM modulated signal which are transmitted over the SCME [11] channel model and they reach each RN. Parameters of the simulation are summarized in Table 1. The simulation is given an interference dataset of 2x10^5 subframes, where the first half will be used for training the model, and the second half for validation. Each subframe of interference contains 6 complex values from 6 RNs. To adapt to the LSTM architecture, the input data of a 12x10 matrix for each subframe is generated, which includes interference values at the past nearest 10 subframes where interference values of each subframe is a 12x1 vector. After input matrix is fed into a trained LSTM network with 20 hidden units, the model outputs a 6x1 output vector, where each of 6 values represents the predicted interference level of each RN of the current subframe. The selection of RN, represented by a 6x1 binary vector, is then based on the value of output vector, where 4 RNs with the least values are chosen. For example, when the predicted
output vector of LSTM network is $g'=[0.1, 1.2, 1.3, 0.8, 0.9, 0.3]$, the selection vector will be $g=[1, 0, 0, 1, 1, 1]$. Fig. 4 indicates this data processing of this model.

**Table 1.** Parameters adopted in the simulations.

| List of parameters | Assumption |
|--------------------|------------|
| Number of UNs (users) | 6 |
| Number of available RNs | 6 with each separated 5MHz apart |
| Codebook of desired users | according to [12] |
| Antennas per user | 1 |
| Antennas per BS | 1 |
| User velocity | 10m/s |
| Carrier frequency | 2.0GHz |
| Channel model for desired users | AWGN |
| SCMA receiver | MPA detector |
| Interference modulation scheme | 4QAM |
| Channel model for interference | 3GPP SCME urban macro |
| Signal to interference ratio | 15dB, 10dB, 6dB |

**Figure 4.** Data processing of the LSTM model in the simulation.

For validation, expected selection vector is produced with a similar process with the utilization of the interference power value of each RN of the current subframe. First, the interference power value of each RN of the current subframe is calculated by summing up the square of real and imaginary part of the corresponding interference data. Secondly, the expected selection vector $g^*$, e.g. $[0, 1, 0, 1, 1, 1]$, which is also a binary vector, is produced by choosing the least value of the interference power. The accuracy of the prediction is calculated by computing the percentage of equability of $g$ to $g^*$, for this example it is acc=66.67%.

This whole process is carried out for $10^5$ subframes and results in a selection matrix $G$ of size $6 \times 10^5$ and an expected selection matrix $G^*$ of the same size. The accuracy of the performance of the LSTM method is calculated by computing the mean value of acc at each subframe.

The BER performance in the case of SIR(signal to interference power ratio)=15dB when using the proposed LSTM scheme for RN selection for different SNR values (Eb/No) is shown in Fig.5. For comparison, another two schemes i.e., “Random” and “MA” are also considered. The “Random” scheme randomly selected 4 RNs out of the 6 RNs in the system. The “MA”(Moving Average) scheme predicts the interference power in the current subframe by averaging the power of 5 most recent subframes and then selects the 4 RNs with the least interference power. It can be observed that in all considered SNR conditions, LSTM outperforms “Random” and “MA” schemes and the “MA” schemes outperforms “Random” scheme. LSTM achieves more than 4 dB gains over the “MA” scheme at BER=$10^{-3}$ and more than 8 dB gains over the “Random” scheme at BER=$2 \times 10^{-3}$. 

*Fig. 4.* Data processing of the LSTM model in the simulation.
Figure 5. BER vs. Eb/No(dB) for SCMA systems using LSTM, “Random” and “MA” resource allocation schemes. SIR=15 dB.

In the case of SIR=10 dB and SIR= 6dB, it still holds that LSTM outperforms “Random” and “MA” schemes as shown in Fig. 6 and Fig. 7. One can notice that as the SIR decreases, i.e., higher interference power is encountered in the system, the BER performance of the system becomes worse and an error floor can be observed when SIR=6 dB and SNR= 18 dB for the proposed LSTM scheme.

Figure 6. BER vs. Eb/No(dB) for SCMA systems using LSTM, “Random” and “MA” resource allocation schemes. SIR=10 dB.

Figure 7. BER vs. Eb/No(dB) for SCMA systems using LSTM, “Random” and “MA” resource allocation schemes. SIR=6 dB.
5. Conclusion
In this paper, we investigate radio resource allocation to avoid inter-cell interference problem in SCMA systems. A deep learning based LSTM network algorithm is proposed to learn the past characteristics of inter-cell interference and predict the current interference level in the system. Comparisons of BER performance with different SIR values, e.g. 6/10/15 dB, has been taken and the simulation results clearly show that the proposed scheme outperforms the conventional MA and “Random” scheme in the aforementioned SIR cases. The efficiency of the proposed scheme in predicting the interference power and selecting radio resources indicates that further researches should be considered in this field.

References
[1] Beek, J.V.D., and Popovic, B.M.: Multiple access with low-density signatures. In: Proc. IEEE Global Telecommunications Conf., pp. 1–6, Honolulu, HI, USA (2009).
[2] Mu, H., Ma, Z., Alhaji, M., et al.: A fixed low complexity message pass algorithm detector for up-link SCMA system. IEEE Wireless Communications Letters, vol. 4, no. 6, pp. 585-588, (2015).
[3] Ma, X., Yang, L., Chen, Z., et al.: Low complexity detection based on dynamic factor graph for SCMA systems. IEEE Communications Letters, vol. 21, no. 12, pp. 2666-2669 (2017).
[4] Wu, H, Xiong, X, Gao, H: Low complexity detection based on selective message passing for SCMA systems. Electronics Letters, 54(8):533-535 (2018)
[5] China Mobile Communications Corporation, Huawei Technologies Co., Ltd, Deutsche Telekom AG, Volkswagen: 5G Service-Guaranteed Network Slicing White Paper.
[6] Liu, Z., Chen, X., Chen, Y., Li, Z.: Deep Reinforcement Learning Based Dynamic Resource Allocation in 5G Ultra-Dense Networks. In: IEEE International Conference on Smart Internet of Things (SmartIoT), pp. 168-174, Tianjin, China (2019).
[7] Mennes, R., Camelo, M., Claeyts, M., and Latré, S.: A neural-network-based MF-TDMA MAC scheduler for collaborative wireless networks. In: Proc. IEEE Wireless Communications and Networking Conference (WCNC), pages 1–6 (2018).
[8] Shi, Q., Razaviyayn, M., Luo, Z., and He, C.: An iteratively weighted MMSE approach to distributed sum-utility maxi-mization for a MIMO interfering broadcast channel. IEEE Transactions on Signal Processing, 59(9) pp. 4331–4340 (2011).
[9] Ghaleb, F. A., Al-Rimy, B. A. S., Almalawi, A., Ali, A. M., Zainal, A., Rassam, M. A. et al: Deep Kalman Neuro Fuzzy-Based Adaptive Broadcasting Scheme for Vehicular Ad Hoc Network: A Context-Aware Approach. IEEE Access (Volume 8) (2020).
[10] Liu, Y., Wang, X., Mei, J., Boudreau, G. et al: Situation-Aware Resource Allocation for Multi-Dimensional Intelligent Multiple Access: A Proactive Deep Learning Framework. IEEE Journal on Selected Areas in Communications, Volume 39, Issue 1 (2021).
[11] Baum, D. S., Hansen, J., Galdo, G. D., Milojevic, M. et al: An interim channel model for beyond-3G systems: extending the 3GPP spatial channel model (SCM). In: Proc. IEEE Vehicular Tech. Conf. (VTC), pp. 3132–3136. vol. 5, Stockholm, Sweden (2005).
[12] 1st 5G Algorithm Innovation Competition-ENV1.0-SCMA. Homepage, http://www.innovateasia.com/5g/en/gp2.html, last accessed 2021/2/19
[13] Al-Tam, F, Correia, N., and Rodriguez, J.: Learn to Schedule (LEASCH): A Deep reinforcement learning approach for radio resource scheduling in the 5G MAC layer. IEEE Access, PP(99):1-1 (2020).
[14] Tang, F., Zhou, Y., Kato, N.:Deep Reinforcement Learning for Dynamic Uplink/Downlink Resource Allocation in High Mobility 5G HetNet. IEEE Journal on selected areas in communications, vol. 38, No. 12 (2020).