5G Channel Forecasting and Power Allocation Based on LSTM Network and Cooperative Communication

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Abstract. In this paper, a forecasted channel system on the basis of Long-Short Term Memory (LSTM) neural network is devised to deal with the problem of gradient disappearance in the Recurrent Neural Network (RNN) specialized in dealing with time series problems. Then, the designed arithmetic is performed and the performances are compared with the real channel, and small Root Mean Square Error (RMSE) is obtained, which shows the high accuracy of the prediction. After that, based on the channel forecasted by using the LSTM network, the power allocation based on cooperative communication is derived, and compare the power results without cooperative communication. For the single-relay cooperative scenarios, a power allocation schema under the end goal to maximize the information transmission rate (ITR) at the destination node is proposed. The realization process of this scheme is constructing the information transmission rate function of the destination node under the condition of setting the total power transmitted is a fixed value by the node. When the ITR of the destination node is the maximum, the source node and relay node achieved the optimal transmission power values. Therefore, system performance is improved by optimizing power allocation method of the transmitting nodes. By comparing with other schemes, it is verified that the power allocation scheme proposed in this paper has better performance and saves system resources.

Keywords: LSTM · 5G · Channel forecasting · Cooperative communication · Power allocation

1 Introduction

In recent years, with the rapid development of global wireless broadband communication technology, the number of mobile user groups has increased rapidly, and there are more and more requirements for the service quality of communication networks and high-speed multimedia applications [1].

Channel forecasting and power allocation are key techniques for wireless communication [2]. If the state of the channel can be predicted, the power in the channel will be allocated reasonably, more power will be distributed on the sub-channel with good

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state, and less power will be distributed on the sub-channel with bad state [3], so as to realize the high efficiency of power allocation [4].

Wireless signal can be considered as a time series, and Recurrent Neural Network (RNN) is one of the most potential tools for time series modeling. The neural network model of RNN adds the features of time series. The hidden layer of the RNN model has feedback edges [5]. The input of each hidden layer includes both the current sample features and the information brought by the previous time series. It can achieve high-accuracy predictions performance [6].

However, RNNs also have some drawbacks. For standard RNN networks, the time span of information that can be used in practice is very limited. When we use information from a relatively recent time point to solve the task of the current moment, RNN can effectively learn the information of the historical moment. However, when we need to use historical information that differs from the current moment information for a long time, the ability of RNN to learn information will be weakened, which is the problem of RNN's gradient disappearance. Long Short Term Memory (LSTM) can be considered as a special form of RNN network, which is superimposed a long term memory function on the RNN, the persistence of the RNN network can be maintained, which allows the long-term dependence of the model on the neural network to be realized [7]. The biggest advantage here is that the LSTM network itself can do the function of remembering information for a long time, which is independent of what it learns through data training. As explained in the previous paragraph, the vanishing gradient phenomenon is ubiquitous in traditional RNN networks [8]. The LSTM network was born to solve this shortcoming. A long-term memory function that keeps information from decaying is superimposed on the traditional RNN network.

In this paper, a 5G channel forecasting system based on the LSTM neural network is proposed, In addition, the cooperative communication is derived to achieve high efficient power allocation based on the forecasted 5G channel by using the LSTM network. The forecasting accuracy of LSTM network and comparison of the performance of power allocation based on cooperative communication with equal power distribution method is presented in Sect. 4.

2 Channel Forecasting Based on LSTM Network

2.1 Introduction and Structure of LSTM Network Model

Long short-term memory network is a variant of recurrent neural network [9], which is mainly used to solve long-term time-dependent problems. For example, in image description, speech recognition, and natural language processing, the LSTM model has performed well and is widely used in academic and industry fields.

Figure 1 shows the structure of a neuron in an LSTM network. The LSTM network is essentially a unidirectional chain structure, and the internal structure of each neuron on the chain is the same, which is the same as the structure of RNN. But the difference of LSTM is that three new structures and special memory units are added to solve the gradient vanishing. The three gate structures are input gate, forget gate and output gate [10]. The gate structure contains the Sigmoid function layer, which can compress the value between 0–1, which helps to remember useful information for a long time or forget redundant information. When the previous data is needed, the activation function will be multiplied by 0 to get 0 output, and this part of the information will not be passed to the next neuron as input [11]. Similarly, when encountering information data that needs to be memorized, it will be multiplied by 1 and still save itself, and then passed to the next neuron as input information. It is through this selective memory or forgetting of information that the LSTM network can save a part of useful information for a long time, and the basis for this phenomenon is the newly added three gate structures and memory units, and the problem of gradient vanishing can be solved [12].

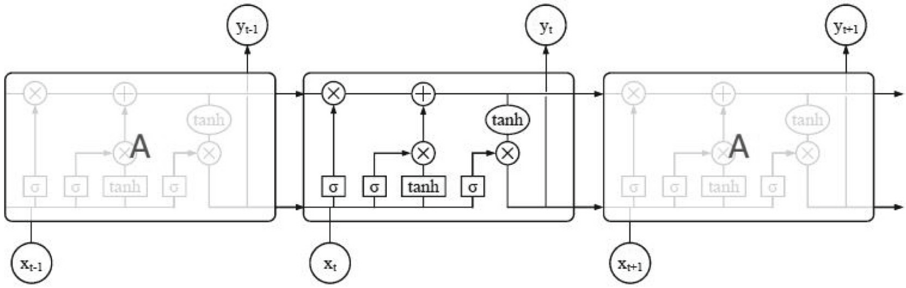

Fig. 1. Structure diagram of LSTM

In Fig. 1, x_t indicates the input at time t, or we can call it the CSI at time t. σ is the Sigmoid function, it is an activation function. $\otimes$ represents the calculation of element multiplication, and the forget gate, input gate and output gate is established by the combination of σ and $\otimes$ together, which are respectively shown from left to right [13]. The information passing through the forget gate will be decided whether it needs to be forgotten, the signal passing through the input gate will be retained and added to the memory unit as a component, and the output of the next hidden state will be determined by the output gate.

2.2 The Training Principle of LSTM

The training method of the LSTM model covers the calculation process of forward calculation and back propagation. The specific calculation process is as follows:

1. Forward calculation process:
   (a) Forget gate: The input vector at time t and the output vector of the output layer at time $t-1$ jointly determine the output state of the forgetting gate at time t. The calculation method is shown in Eq. (1).

$$f_t = \sigma\left(W_f \cdot (y_{t-1}, x_t) + b_f\right) \tag{1}$$

   where: f_t is the output vector at time t, σ is the activation function, W_f is the weight matrix, concated by matrix W_{fy} and matrix W_{fx}, y_{t-1}, x_t are the output

vector of the output layer at time $t-1$ and the input vector of the input layer at time t, respectively. b_f is the bias term.
Among them, W_f can be presented as:

$$\begin{aligned}(W_f)\begin{pmatrix}y_{t-1}\\x_t\end{pmatrix} &= (W_{fy}W_{fx})\begin{pmatrix}y_{t-1}\\x_t\end{pmatrix}\\ &= W_{fy}y_{t-1}+W_{fx}x_t\end{aligned} \tag{2}$$

(b) Input gate: The input gate can be represented by the Eq. (3), and the meanings represented by the symbols in the formula are similar to those of the forget gate, which will not be repeated here.

$$i_t = \sigma\left(W_i \cdot (y_{t-1}, x_t) + b_i\right) \tag{3}$$

(c) Memory unit: The state of the memory unit at the current moment can be calculated in two steps. First, the output at time $t-1$ and the input at time t are used to calculate the state $\hat{c}_t$ of the current input unit. Its calculation expression can be expressed as:

$$\hat{c}_t = tanh\left(W_c \cdot (y_{t-1}, x_t) + b_c\right) \tag{4}$$

Then calculate the memory cell state c_t at the current moment:

$$c_t = f * c_{t-1} + i_t * \hat{c}_t \tag{5}$$

The $*$ symbol in the formula is the multiplication operation between each element. The unit state $\hat{c}_t$ input by the LSTM at the current moment and the long-term memory c_{t-1} are combined through the memory unit.

(d) Output gate:

$$o_t = \sigma\left(W_o \cdot (y_{t-1}, x_t) + b_o\right) \tag{6}$$

$$y_t = o_t * tanh(c_t) \tag{7}$$

y_t represents the final output of the LSTM model at the current time, that is, the spectral prediction value at time t. It can be seen from Eq. (7) that the output of the output gate and the state of the memory unit at the current moment jointly determine the value of y_t.

2. Back propagation process of error:
Similar to the RNN model, the calculation of the error back propagation of the LSTM model also uses the value of the error term σ, and according to the calculated error term, the gradient descent method is used to update the weights. In the training process of the LSTM model, there are 4 groups of weights that the model needs to learn, and the specific learning parameters are shown in Table 1:
The weight matrix plays a different role in the derivation process of backpropagation, so it is divided as follows:

$$\begin{aligned}W_o &= [W_{oy}, W_{ox}]\\ W_f &= [W_{fy}, W_{fx}]\\ W_i &= [W_{iy}, W_{ix}]\\ W_c &= [W_{cy}, W_{cx}]\end{aligned} \tag{8}$$

Table 1. Learning parameters

Module	Weight matrix	Bias item
Output gate	W_o	b_o
Forget gate	W_f	b_f
Input gate	W_i	b_i
Memory unit	W_c	b_c

Assuming that the error (loss function) is E, and the output at time t is y_t, then the error term δ_t of the output layer at time t is:

$$\delta_t = \frac{\partial E}{\partial y_t} \tag{9}$$

For the above four weight matrices, there are four weighted inputs, which correspond to f_t, i_t, c_t and o_t at time t, respectively. Let their corresponding error terms be δ_{ft}, δ_{it}, δ_{ct} and δ_{ot}, respectively, then:

$$\begin{aligned}\delta_{o_t}^T &= \frac{\partial E}{\partial (W_o \cdot (y_{t-1}, x_t) + b_o)} \\ &= \frac{\partial E}{\partial y_t} \cdot \frac{\partial y_t}{\partial o_t} \cdot \frac{\partial o_t}{\partial (W_o \cdot (y_{t-1}, x_t) + b_o)} \\ &= \delta_t^T * tanh(c_t) * o_t * (1 - o_t)\end{aligned} \tag{10}$$

In the same way, the error term of forget gate, input gate and memory cell can be known from the chain rule.
The error propagation along the time direction is to calculate the error term δ_{t-1} at time t_1, and the expression of δ_{t-1} is:

$$\delta_{t-1} = \delta_{o_t}^T W_{oy} + \delta_{f_t}^T W_{fy} + \delta_{i_t}^T W_{iy} + \delta_{\hat{c}_t}^T W_{cy} \tag{11}$$

The calculation formula for the propagation of the error term to the upper layer can be expressed as:

$$\begin{aligned}\delta_{t-1}^l &= \frac{\partial E}{\partial (W \cdot (y_t, x_t) + b)} \\ &= (\delta_{o_t}^T W_{ox} + \delta_{f_t}^T W_{fx} + \delta_{i_t}^T W_{ix} + \delta_{\hat{c}_t}^T W_{cx}) * f'(W \cdot (y_t, x_t) + b)\end{aligned} \tag{12}$$

where $W \cdot (y_t, x_t) + b)$ represents the weighted input of layer $l-1$, and f is the activation function of layer $l-1$.

Taking the output gate as an example, the calculated error term is used to calculate the gradient of each weighting matrix and the gradient of the bias term at time t. The calculation can be expressed as:

$$\frac{\partial E}{\partial W_{oy,t}} = \frac{\partial E}{\partial (W_o \cdot (y_{t-1}, x_t) + b_o)} \cdot \frac{\partial (W_o \cdot (y_{t-1}, x_t) + b_o)}{\partial W_{oy,t}} = \delta_{o_t} y_{t-1}^T \tag{13}$$

$$\frac{\partial E}{\partial W_{ox,t}} = \frac{\partial E}{\partial(W_o \cdot (y_{t-1}, x_t) + b_o)} \cdot \frac{\partial(W_o \cdot (y_{t-1}, x_t) + b_o)}{\partial W_{ox,t}} = \delta_{o_t} x_{t-1}^T \tag{14}$$

$$\frac{\partial E}{\partial b_{o,t}} = \frac{\partial E}{\partial(W_o \cdot (y_{t-1}, x_t) + b_o)} \cdot \frac{\partial(W_o \cdot (y_{t-1}, x_t) + b_o)}{\partial b_{o,t}} = \delta_{o_t} \tag{15}$$

The final gradient is the sum of the gradients at each time:

$$\frac{\partial E}{\partial W_{oy}} = \sum_{j=1}^{t} \delta_{o_j} y_{j-1}^T; \tag{16}$$

$$\frac{\partial E}{\partial W_{ox}} = \sum_{j=1}^{t} \delta_{o_j} x_j^T \tag{17}$$

$$\frac{\partial E}{\partial b_o} = \sum_{j=1}^{t} \delta_{oj} \tag{18}$$

In the same way, the weight matrix and the gradient of the bias term of the forget gate, input gate and memory unit can be obtained.

3 Power Allocation Based on Cooperative Communication

In cooperative communication, nodes cooperate with each other, which can not only expand the communication range [14], but also improve the information transmission rate of the system. The research on resource allocation in cooperative communication mainly focuses on power allocation. By rationally allocating the power of nodes, the system performance can be improved while the power consumption can be reduced [15].

When a relay node cooperates with other nodes to transmit information, it should not only consider improving the system performance, but also consider when to cooperate, with whom and how to cooperate [16]. Compared with the straight forward communication link, cooperative communication has better transmission quality and channel capacity, but the structure of cooperative communication is complex and the amount of calculation is large [17]. The direct transmission link has a simple structure and low complexity. Due to the limited wireless communication resources, the main goal of cooperative communication is to improve the performance of the communication network and allocate power reasonably under the premise that the total power of the wireless communication system is constrained [18].

3.1 Cooperative Communication System Model

As shown in Fig. 2, the system model includes three nodes, which is source node S, relay node R and destination node D. There are two transmission links in the communication

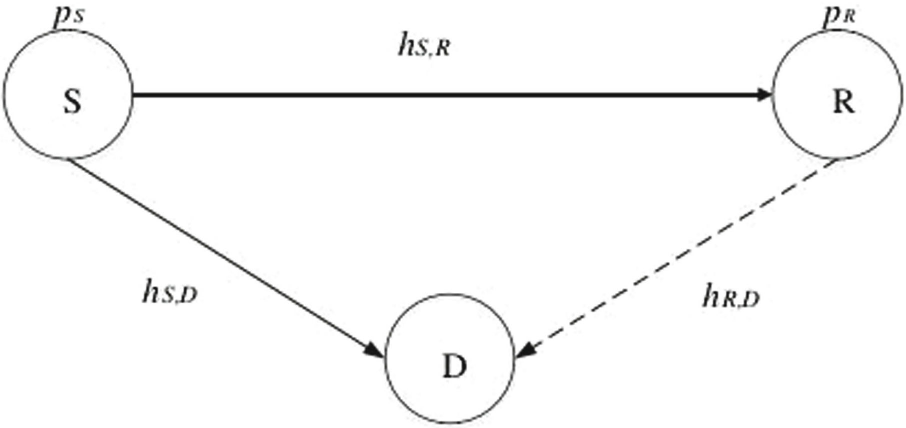

Fig. 2. Cooperative communication system model

with different transmission time: the first link at time one, node S sends signals to the node R and the node D directly; at the second link at time two, the node R transmits the signal to the node D through DF transmission [19]. The node D cooperates and decodes the signals received from the node S and node R to obtain diversity gain.

In the system model, the channel coefficients of the three links are $h_{S,D}$, $h_{S,R}$, and $H_{r,d}$, respectively. The noises of the three links are independent of each other and are Gaussian white noise with 0 mean and variance σ^2. p_R is the transmission power from node R. In the first time slot, the information transmission rates $R_{S,D}$ and $R_{R,D}$ obtained by the node R and node D are expressed as:

$$R_{S,D} = \frac{1}{2}log_2(1+\gamma_{S,D})$$
$$R_{S,R} = \frac{1}{2}log_2(1+\gamma_{S,R}) \tag{19}$$

Among them, $\frac{1}{2}$ in the equation is because the whole transmission process includes two transmission time slots. The S-D link has a SNR of $\gamma_{S,D} = \frac{p_S H_{S,D}}{\sigma^2}$, and the S-R link has a SNR of $\gamma_{S,R} = \frac{p_S H_{S,R}}{\sigma^2}$.

In the second time slot, the information transmission rate $R_{R,D}$ obtained by the destination node is expressed as:

$$R_{R,D} = \frac{1}{2}log_2(1+\gamma_{R,D}) \tag{20}$$

where the SNR of R-D link is $\gamma_{R,D} = \frac{p_R H_{R,D}}{\sigma^2}$.

3.2 Power Allocation

Introduction to Power Allocation. Power allocation is to calculate the optimal power allocation factor with the goal of maximizing the QoS performance at the destination node under the condition of constraining the total power of the node [20]. In the problem of power allocation, this paper takes the information transmission rate as the optimization goal to reduce power consumption when the system performance is optimal.

1. Define Variables
   The node power allocation vector is expressed as:
   $$P = [p_S, p_R] \tag{21}$$
   Compare the information transmission rate of the relay node and the destination node, and express the minimum value $f(p_S, p_R)$ as
   $$f(p_S, p_R) = \min(R_{S,D} + R_{R,D}, R_{S,D}) \tag{22}$$
2. Target Optimization
   In the system model, the proposed power allocation scheme should not only ensure the maximum information transmission rate of the destination node, but also minimize the power consumption of the entire transmission process and reduce the power consumption overhead. The optimization objective function is represented by the following equation:
   $$\max_{p_S, p_R} f(p_S, p_R) \tag{23}$$
   The constraints are expressed as:
   $$p_S + p_R \leq p_{tot} \tag{24}$$
   $$log^2(1 + p_S H_{S,D}) + log^2(1 + p_R H_{R,D}) \geq log^2(1 + p_S H_{S,R}) \tag{25}$$
   $$p_S \geq 0, p_R \geq 0 \tag{26}$$
   Among them, $\sigma^2 = 1$, Eq. (23) is the optimization objective function, Eq. (24) is the constraint condition of the transmission power from node S and node R, Eq. (25) is the maximum value reached by the destination node rate, Eq. (26) is the transmission power values of node S and node R are greater than 0.
   On the foundation of above three constraints, the optimization state is described as, under the premise of ensuring that the power of the node is positive and constraining the total transmit power of the node, the goal is to maximize the information transmission rate of the destination node, so as to obtain the optimal relationship between the node S and node R.

3.3 The Power Allocation Algorithm for Cooperative Communication

In order to decline the squander of resources and improve the system performance, a power allocation scheme is proposed in the single-relay cooperative communication model. The power allocation scheme is to establish a convex optimization function of the maximum information transmission rate of the destination node under the constraint of ensuring the total transmit power [21], and use the Lagrangian function to optimize the transmission power of node S and node R.

The steps of the algorithm are as follows:

Step1: The Lagrange equations for optimizing objective Eqs. (22) to (24) are expressed as:

$$\begin{aligned} L(p_S, p_R) =& f(p_S, p_R) + \lambda[log_2(1 + p_S H_{S,D}) + log_2((1 + p_R H_{R,D}) \\ & - log_2(1 + p_S H_{S,R})] + \mu(p_S + p_R - p_{tot}) \end{aligned} \tag{27}$$

where $\lambda \geq 0$ is the Lagrange multiplier under power constraints.

Step2: According to the Karush-Kuhn-Tucker condition, set the partial derivatives of $L(p_S, p_R)$ to p_S and p_R to 0 respectively. The optimal solutions p_S^* and p_R^* should satisfy the following equations:

$$\frac{\partial L}{\partial p_S^*} = \frac{1}{2ln2}\left[\frac{H_{S,D} + 2\lambda H_{S,D}}{(1 + p_S H_{S,D})} - \frac{2\lambda H_{S,R}}{(1 + p_S H_{S,R}})\right] + \mu \tag{28}$$

$$\frac{\partial L}{\partial p_R^*} = \frac{H_{R,D}(1 + 2\lambda)}{2ln2(1 + p_R H_{R,D})} + \mu \tag{29}$$

Step3: In the optimization Eq. (30), under the condition that the total power of the node is constrained, when the information transmission rate of the destination node reaches the maximum, the optimal power p_S^* and p_R^* of the source node and the relay node are respectively:

$$p_S^* = \min\left(\frac{1 + 2\lambda}{2\mu ln2} - \frac{1}{H_{R,D}, p_{tot}}\right) \tag{30}$$

$$p_R^* = \max\left(\frac{H_{R,D}(1 + 2\lambda)}{2ln2(1 + p_R H_{r,d})} + \mu\right)^+ \tag{31}$$

where, $(\cdot)^+ = \max(\cdot, 0)$

Equations (28) to (31) are the optimal solutions of the optimization problem (23).

4 Simulations and Performance Analysis

4.1 5G Channel Forecasting Based on LSTM Network

In this section, the simulation of 5G channel forecasting based on LSTM is derived.

The parameters of simulated channels are shown in Table 2. We selected 10000 channels, and performed average value of 10000 times forecasting. During the forecasting, first 90% of observations is used to train the model, and last 10% data is used

Table 2. Simulation parameters

Frequency (GHz)	28.0	Bandwidth (MHz)	800
TXPower (dBm)	30.0	Environment	NLOS
Scenario	UMi	Pressure (mBar)	1013.25
Humidity	50	Temperature (Celsius)	20.0
Rain Rate (mm/hr)	0.0	Polarization	Co-Pol
Foliage	No	DistFol (m)	0.0
Foliage Attenuation (dB)	0	TX Array Type	URA
RXArray Type	URA	Num of TX Elements	64
Num of RX Elements	64	TXAziHPBW	10
TXElvHPBW	10	RXAziHPBW	10
RXElvHPBW	10		

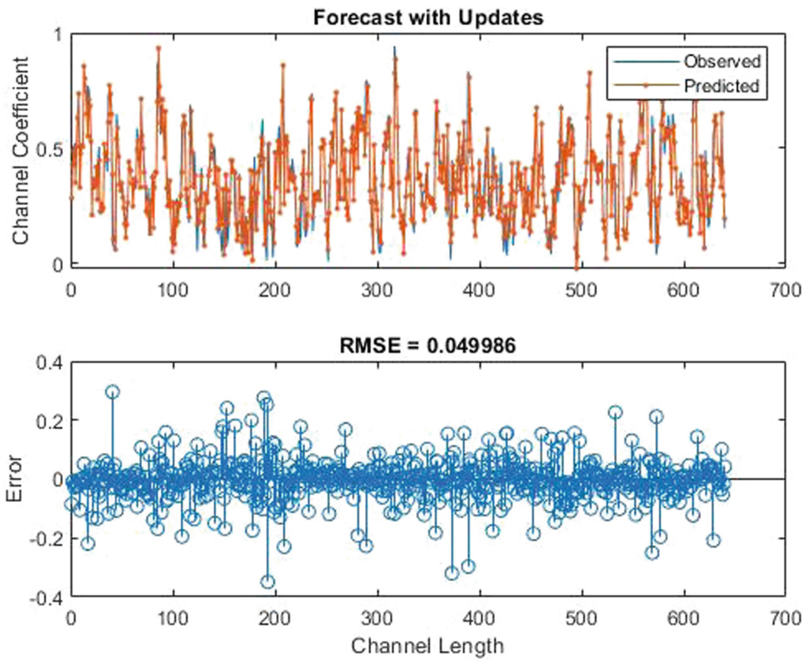

Fig. 3. Comparison and RMSE of forecasting by using actual observation

to test. Through experiments, we selected the optimal LSTM network parameters, used a two-layer neural network with 330 hidden units, and performed 2000 iterations of training.

Then, we forecasted values for multiple time steps, and updated the network with each forecasting. After each step of forecasting, use the previous forecasted value as the input to the function. Because the CSI has been obtained, the actual value of the time step between each forecasting is used to replace the forecasted value to update the network state. The comparison of forecasting accuracy and RMSE is performed in Fig. 3. The RMSE is about 0.05. We can conclude that our optimized model parameters for LSTM network can achieve a relatively high forecasting accuracy.

4.2 Power Allocation Based on Cooperative Communication

Information Transmission Rate of Destination Node vs Power of Source Node. The initial value of the power of the source node is set to 10 dBm, which is linearly increased to 20 dBm according to the step size of about 1 dBm. The influence of the transmit power of the source node on the information rate of the destination node under different power schemes is analyzed as shown in Fig. 4.

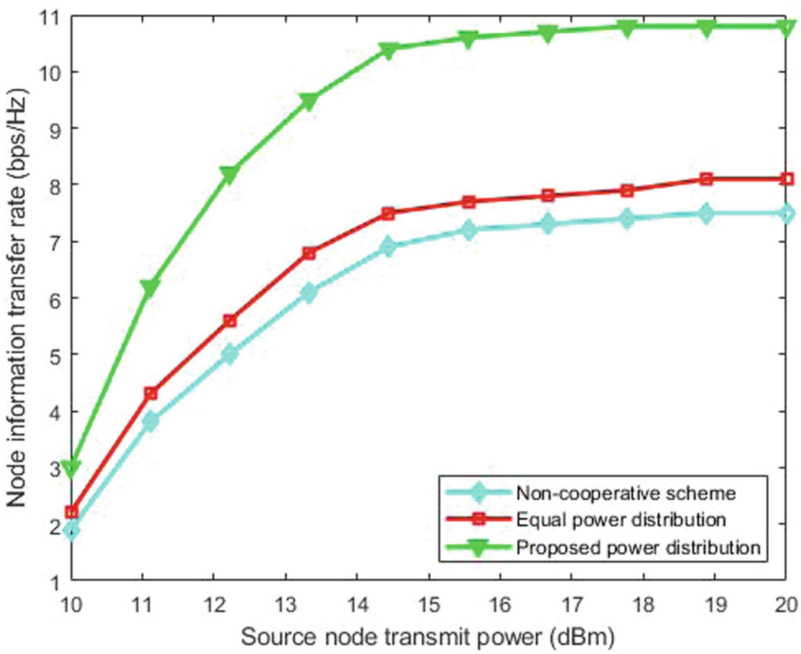

Fig. 4. Information transmission rate of destination node vs power of source node

Figure 4 describes the change of the information rate of the destination node when the power of the source node changes. The scheme in this paper can maximize the information rate of the destination node under the premise of constraining the total transmit power of the node, and effectively reduce the transmit power of the source node. Compared with the other two schemes, this scheme can improve the information transmission rate of the destination node, especially when the transmit power is small.

Information Transmission Rate of Destination Node vs Power of Relay Node. The initial value of the relay node power is set to 10 dBm, and it is linearly increased to 20 dBm in steps of about 1 dBm. Compare the power allocation scheme proposed in this paper with the equal power distribution, and study the influence of the relay node power on the information rate of the destination node as shown in the Fig. 5 shown.

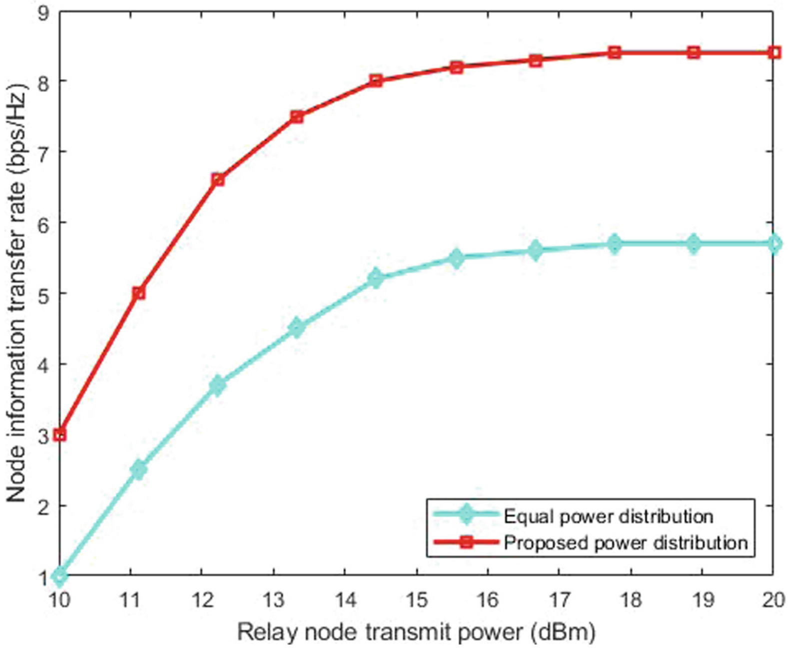

Fig. 5. Information transmission rate of destination node vs power of relay node

Figure 5 describes the change of the information rate of the destination node when the power of the relay node changes. First of all, the figure shows that in the process of linear increase of relay node transmit power, the change of destination node information rate shows an upward trend, which is because with the increase of relay node transmit power, the power used for information transmission becomes larger, Therefore, the information transmission rate at the destination node is improved. Secondly, compared with the equal power scheme, the proposed scheme obtains better information rate of the destination node. The proposed scheme not only improves the information transmission rate of the destination node, but also reduces the power consumption of the relay node, due to cooperative diversity helps to improve the information transmission rate at the destination node. In addition, Fig. 5 presents that when the relay node power is low, both power allocation schemes improve the information transmission rate of the destination node. However, the scheme proposed in this paper has a higher information transmission rate of the destination node when the transmit power of the relay node changes, reflecting the constraints on the total power of the node. The power allocation scheme proposed in this paper can maximize the information rate of the destination node.

Information Transmission Rate of Destination Node vs Distance of Relay Node. The initial value of the relay node position is set to 20 m, and linearly increases to 110 m in steps of 10 m. Comparing the power allocation scheme proposed in this paper with the equal power allocation scheme, the difference between the information transmission rate of the destination node and the position of the relay node The relationship is shown in Fig. 6.

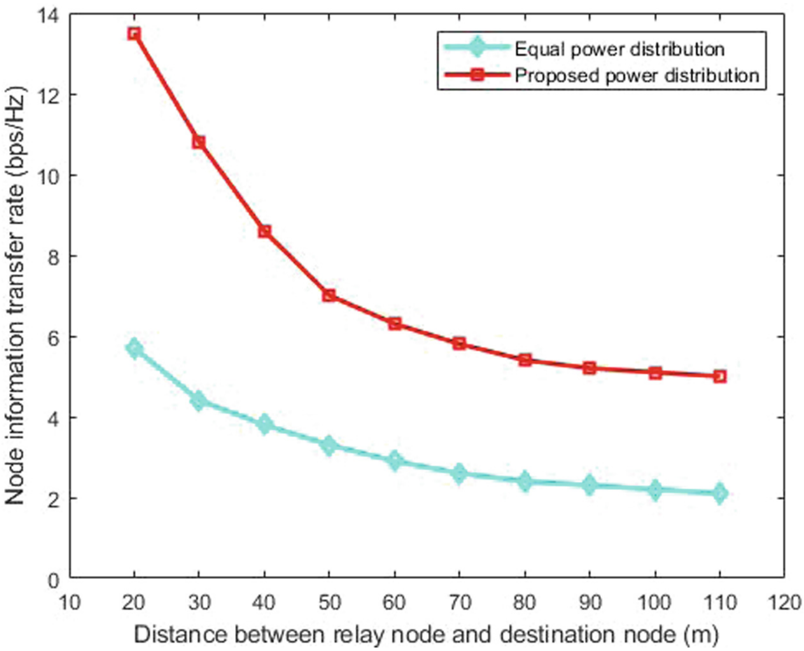

Fig. 6. Information transmission rate of destination node vs distance of relay node

Figure 6 presents the change in the information rate of the destination node when the position of the relay node changes. Compared with the equal power allocation scheme, when the relay node is located closer, the information rate of the destination node decreases rapidly with its increase. When the position of the successor node is very large, the existence of interference limitation makes the information transmission rate of the destination node tend to a stable value. The proposed scheme is better than the equal power allocation scheme in response to the change of the information rate of the destination node.

5 Conclusion and Future Work

In this paper, the simulated 5G channel is forecasted by using LSTM network. Based on that, cooperative communication is proposed to improve the performance of wireless communication. The optimal LSTM model parameters are obtained to achieve the RMSE about 0.05 of testing data set. In addition, a power allocation algorithm based on cooperative communication is proposed and the comparisons of proposed scheme with non-cooperative system and equal power allocation scheme discussed.

The LSTM model in the recurrent neural network as the main analysis tool is implemented in the paper. However, the LSTM neural network has a complex structure, which requires a lot of experiments and theoretical analysis to select the type of activation function for the network level, which optimization algorithm to use, and even to design several layers of neural network structure. The selection of hyperparameters in wireless communication channel forecasting using LSTM network is also an important follow-up research work in this paper. In addition, the work of this paper is mainly based on the relay selection strategy. Research in other directions, such as power control and coding cooperation, is also the focus of cooperative communication. In addition to the capacity-maximizing power allocation strategy mentioned in this paper, we can also study the power consumption of different forwarding methods, the probability of interruption, and the power allocation strategy when the channel quality meets a certain standard, and explore the power allocation from the perspective of various combinations of improvement.

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