Channel Prediction And Power Optimization For Smart HSR Communication Networks Based On Deep-Learning Networks

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Abstract- *For a high-speed railway relay downlink communication system based on short-packet transmission, the problem of maximizing the minimum user throughput by jointly optimizing the transmission packet length and the transmission power control of the relay device. The optimization problem is a nonconvex and mixed-integer one that is difficult to obtain an optimal solution, and a low-complexity algorithm is proposed to obtain the solution to the joint optimization problem. Intelligent channel prediction plays a key role in artificial intelligence (AI)-optimized or AI-native communication networks for smart high-speed railways (HSRs). The spatial-temporal prediction of channel state information (CSI) and channel statistical characteristics (CSCs) based on deep-learning (DL) for the future smart HSR communication network. A propagation-graph simulation method is used to generate datasets of CSI and CSCs for massive multiple-input multiple-output (mMIMO) channels in a HSR cutting scenario, and realistic channel measurements are used to validate the datasets. Then, single-step ahead and multi-step ahead prediction problems are formulated with the consideration of both spatial and temporal information hidden in the datasets. Finally, the performance of the Conv-CLSTM model is evaluated in terms of prediction accuracy and space and time computational complexity. The evaluation results show that the proposed model has high prediction accuracy but acceptable computational complexity.*

Keywords- high-speed railways (HSRs), channel state information (CSI), channel statistical characteristics (CSCs)

I. INTRODUCTION

In order to meet the demand of high-speed data transmission, the application of 5G technology in high-speed railway (HSR) scenarios is gaining more and more attention. To ensure the safe operation and the high quality of experience of the users, the wireless communication technology plays an important role in HSR system. The downlink resource allocation problem in HSR downlink orthogonal frequency division multiple access (OFDMA) system with a cellular/relay integrated network architecture was investigated and an equivalent one-stage programming. The secure transmission from the roadside base stations to the vehicle stations on the top of the train was considered, and the eavesdropping user is a mobile unmanned aerial vehicle, where the objective is to maximize the sum of the minimum security rate of each time slot. The transmission performance of wireless links between the base station and the access point on the roof of the train was considered and the quality of service (QoS) distinguished power allocation algorithm was derived to achieve the largest achievable rate region. These works mainly concern the direct communication between the base station and the vehicle stations. However, the penetration losses caused by train carriage and Doppler shift are more severe at millimeter wave frequencies. Therefore, it is widely accepted that a mobile relay-based network architecture is one of the most desirable solutions to the above problem.

In the mobile relay network, the link between the base station and relay device uses frequencies below 6 GHz, while the link between the relay device and user uses millimeter wave frequencies. There are several advantages of mobile relay in HSR communication compared with the conventional direct point to point communication. Firstly, HSR has sufficient power and a large space to support the mobile relay stations with multiple antennas. Secondly, mobile relay offers new chance for performance enhancement by the higher frequency (e.g., millimeter wave), especially for a large number of passengers in the carriage in a static environment. Thirdly, the lower frequency in the link between the train and ground can reduce Doppler shift, which makes the mobile relay stations stronger processing power and the link more reliable.

There are many researches on mobile relay network in the existing literature. When mobile relay nodes cooperated, the system-level simulation of HSR, the results showed that the cooperation of relay nodes could significantly improve the user rate. In, the system performance of average symbol error rate for the two relays railway networks was analyzed, and decode-and-forward (DF) protocol was adopted by partial differential modulation. The simulation results showed that the system had the best performance, when two relay nodes were in the same location. In, the HSR communication system with mobile relay technology and OFDMA to serve users was considered, and how to minimize the total power consumption of base stations and relay nodes under the desired QoS of users was investigated. The optimal subcarrier and power allocation scheme was derived by the Lagrange dual method, then a low-complexity sub-optimal algorithm based on the Hungarian algorithm was proposed. A novel two-hop mobile relay architecture for high-speed trains was considered, two relay structures (several relay nodes in a railway carriage and a single relay node with multiple antennas) and two relay modes (amplifyand-forward and DF) were studied. A new broadband data access technology using multiple input and multiple output (MIMO) technology, mobile relay and millimeter wave band was proposed to provide service for train passengers in highspeed environment. The HSR communication system based on relay was considered, and the relay node operated in full duplex mode. The goal was to maximize the network capacity by allocating spectrum resources, and the formulated problem was a non-convex optimization one about the spectrum resource allocation. A sequential quadratic programming algorithm based on Lagrange function was proposed, which could effectively solve the bandwidth allocation problem of base stations and relay nodes.

The 5G-based Internet of Things technology can provide ultra-reliable low-latency communication (URLLC) for HSR system, and improve the QoS of the passengers. For URLLC, ultra-reliable means high stability of the network, and low-latency requires minimal end-to-end time delay. In the URLLC scenario, the latency is generally 1-10 milliseconds. At present, most physical layer designs rely largely on long blocklengths, which make the transmission rate close to Shannon capacity. To support low-latency communication, the shor-packet data with finite blocklength codes is considered to reduce the transmission latency. Compared with Shannon capacity for infinite blocklength, the decoding error probability of the receiver for finite blocklength transmission cannot be ignored due to the short blocklength. The accurate approximate value of the information rate of the limited blocklength in the additive white Gaussian noise (AWGN) channel, which considered error probability and blocklength. Nonorthogonal multiple access (NOMA) in short-packet communications was compared with orthogonal multiple access (OMA), which could reduce the transmission latency of physical layer. The closed-form expression for the block error rate in NOMA was derived, and the near-optimal scheme about power allocation and blocklength was given. A multiuser downlink network model in the finite blocklength regime was considered, the optimal power allocation algorithm was proposed to maximize the normalized sum throughput under statistical QoS constraints. In, a downlink multiple-input single-output (MISO) OFDMA URLLC system with short packet transmission was considered, the proposed resource allocation algorithm was used to maximize the weighted sum throughput with QoS constraints regarding the number of transmitted bits and delay.

Smart high-speed railways (HSRs) have become a significant direction of future HSR development, which aims to improve the railway operation safety, economical efficiency, convenience, comfortableness, and environmental friendliness. The smart HSRs will fully utilize new generation information technologies such as big data, artificial intelligence (AI), Internet of Things (IoT), next-generation mobile communications, and cloud computing. The smart HSR communication network is one of essential parts in the entire smart HSR system, which will be used for satisfying higher and higher communication requirements of railway operation and passenger experience in terms of data rate, capacity, latency, and reliability. Undoubtedly, traditional dedicated railway networks are unable to undertake this task. Fifth-generation (5G) technologies such as massive multiple-input multiple-output (mMIMO), millimeter wave (mmWave), and ultrareliable low latency communications (URLLC) have been recommended for the smart HSRs and an innovative 5G for railway (5G-R) network was discussed. The 5G-R network can be possible to meet the requirements of high throughput, high reliability, and low latency for smart HSR communications. Therefore, it has been regarded as a candidate for the future smart HSR communication network.

II. LITERATURE SURVEY

Een-Kee Hong, Inkyu Lee, “6G R&D vision: Requirements and candidate technologies”, 2022 the Korean Institute of Communications and Information Sciences (KICS), which is the largest information and communication technology institute in Korea, has been active in working towards development and standardization of mobile communication technology. In response to the need to meet upcoming 6G technical challenges in innovative applications such as hologram telepresence, extended reality (XR), digital twin, and connected robotics, the KICS 6G research initiative (KICS 6GRI) group has been created to establish a vision for key 6G technologies and identify research trends and directions. This article, therefore, covers major performance indicators and requirements envisioned by the KICS. In addition, we provide a comprehensive discussion of various candidate 6G technologies including (sub-)terahertz (THz), intelligent reflecting surface (IRS), artificial intelligence (AI)-based techniques, and non-terrestrial network (NTN).

J. Hoydis, F. A. Aoudia, A. Valcarce, and H. Viswanathan, "Toward a 6G AI-native air interface", 2021 each generation of cellular communication systems is marked by a defining disruptive technology of its time, such as OFDM for 4G or Massive MIMO for 5G. Since AI is the defining technology of our time, it is natural to ask what role it could play for 6G. While it is clear that 6G must cater to the needs of large distributed learning systems, it is less certain if AI will play a defining role in the design of 6G itself. The goal of this article is to paint a vision of a new air interface that is partially designed by AI to enable optimized communication schemes for any hardware, radio environment, and application.

C. Xue, T. Zhou, H. Zhang, L. Liu, and C. Tao, "Deep learning based channel prediction for massive MIMO systems in high-speed railway scenarios", 2021 the prediction model based on deep learning for the wireless channel characteristics of massive MIMO systems in high-speed railway (HSR) scenarios. Based on the propagation graph theory, we simulate the massive MIMO channel in a HSR cutting scenario. The datasets of spatial-temporal channel characteristics, involving channel state information, Ricean K-factor, delay spread, and angle spread, are generated for the model training and testing, and two kinds of prediction problem formulations, such as single-step and multi-steps, are designed. By considering both the spatial and temporal correlation properties in HSR massive MIMO channels, a novel channel prediction model that combines the convolutional long short-term memory (CLSTM) and convolutional neural network (CNN) is proposed and called as Conv-CLSTM. The hyperparameters of Conv-CLSTM are determined by comparative experiments and autocorrelation and similarity analysis. According to the performance evaluation, it is showed that the proposed Conv-CLSTM outperforms the other deep learning and machine learning models.

T. Zhou, Y. Yang, L. Liu, C. Tao, and Y. Liang, "A dynamic 3-D wideband GBSM for cooperative massive MIMO channels in intelligent high-speed railway communication systems", 2021 coordinated multipoint (CoMP) and massive multiple-input multiple-output (mMIMO) are two of promising technologies in future intelligent high-speed railway (HSR) communication systems, whose performance is fundamentally determined by the characteristics of cooperative mMIMO channels. This article proposes a dynamic three-dimensional (3-D) wideband geometry-based stochastic model (GBSM) for HSR cooperative mMIMO channels. The proposed GBSM employs a sphere model and two elliptic-cylinder models to describe common and uncommon clusters for different links, and integrates the dynamic cluster evolution in both time and array domains. Statistical properties of the cooperative mMIMO model are investigated, such as multi-link spatial cross-correlation function and sum rate capacity. A corresponding dynamic 3-D wideband simulation model for the HSR cooperative mMIMO channel is also proposed. Finally, numerical results of the statistical properties are analyzed, and the proposed model is validated by realistic HSR channel measurement data, in terms of dual-link spatial cross-correlation and channel capacity. This model is more practical and will be helpful for facilitating the design and performance evaluation of future intelligent HSR communication systems.

B. Ai, A. F. Molisch, M. Rupp, and Z.-D. Zhong, "5G key technologies for smart railways", 2020 railway communications has attracted significant attention from both academia and industries due to the booming development of railways, especially high-speed railways (HSRs). To be in line with the vision of future smart rail communications, the rail transport industry needs to develop innovative communication network architectures and key technologies that ensure high-quality transmissions for both passengers and railway operations and control systems. Fifth-generation (5G) technologies could be a promising solution to dealing with the design challenges on high reliability and high throughput for HSR communications. Based on our in-depth analysis of smart rail traffic services and communication scenarios, we propose a network slicing architecture for a 5G-based HSR system. With a ray tracing-based analysis of radio wave propagation characteristics and channel models for millimeter wave (mm Wave) bands in railway scenarios, we draw important conclusions with regard to appropriate operating frequency bands for HSRs. My margin Specifically, we have identified significant 5G-based key technologies for HSRs, such as spatial modulation, fast channel estimation, cell-free massive multiple-input-multiple-output (MIMO), mm Wave, efficient beam forming, wireless backhaul, ultra reliable low latency communications, and enhanced handover strategies.

T. Zhou, Y. Wang, C.-X. Wang, S. Salous, L. Liu, and C. Tao, "Multifeature fusion based recognition and relevance analysis of propagation scenes for high-speed railway channels", 2020 multi-feature fusion based propagation scene recognition model for high-speed railway (HSR) channels and presents the channel relevance analysis of HSR scenes. Extensive field measurement data in typical HSR scenes, including rural, station, suburban and multi-link scenes, are collected with the assist of railway long-term evolution (LTE) networks. The datasets of space-time-frequency channel features, involving Ricean K-factor, root mean square delay spread, Doppler spread, and angle spread, are generated for the model training and testing as well as the relevance analysis. The proposed model merges a weighted score fusion scheme into the deep neural network (DNN) in order to adaptively determine the optimal weights for each feature stream. This weighted score fusion based DNN model is implemented and evaluated in terms of accuracy, confusion matrix, F-score, and receiver operating characteristic (ROC) curve, which exhibits better performance than other machine learning models like random forest, support vector machine (SVM), k-nearest neighbor (KNN), and weighted KNN. In addition, the channel relevance of HSR scenes is analyzed from perspectives of high-dimensional distribution distance and joint correlation of multiple features. Two metrics, Wasserstein distance and correlation matrix collinearity, are used in the analysis. Statistical results are provided, which reveals the relatively strong channel relevance between the multi-link and suburban scenes.

J. Huang, C. X. Wang, L. Bai, J. Sun, and Y. Yang, “A big data enabled channel model for 5G wireless communication systems”, 2020 the standardization process of the fifth generation (5G) wireless communications has recently been accelerated and the first commercial 5G services would be provided as early as in 2018. The increasing of enormous smartphones, new complex scenarios, large frequency bands, massive antenna elements, and dense small cells will generate big datasets and bring 5G communications to the era of big data. This paper investigates various applications of big data analytics, especially machine learning algorithms in wireless communications and channel modeling. We propose a big data and machine learning enabled wireless channel model framework. The proposed channel model is based on artificial neural networks (ANNs), including feed-forward neural network (FNN) and radial basis function neural network (RBF-NN). The input parameters are transmitter (Tx) and receiver (Rx) coordinates, Tx–Rx distance, and carrier frequency, while the output parameters are channel statistical properties, including the received power, root mean square (RMS) delay spread (DS), and RMS angle spreads (ASs). Datasets used to train and test the ANNs are collected from both real channel measurements and a geometry based stochastic model (GBSM). Simulation results show good performance and indicate that machine learning algorithms can be powerful analytical tools for future measurement-based wireless channel modeling.

X. Zhao et al., “Playback of 5G and beyond measured MIMO channels by an ANN-based modeling and simulation framework,” IEEE J. Sel. Areas Commun., vol. 38, no. 9, pp. 1945–1954, Sep. 2020 an artificial neural network (ANN) based channel modeling and simulation framework to playback a measurement channel to overcome the shortcomings of traditional geometry based stochastic modelling (GBSM) and simulation approach which is unable to predict a time or position-varying channel to match with real environment. Secondly, we implement the framework based on channel measurements performed at 28 GHz in a large waiting hall at Qingdao high-speed railway station, China. Thirdly, we validate the proposed framework by comparisons of the large scale channel parameters (LSCPs) and small scale channel parameters (SSCPs) extracted from the measured, ANN and GBSM simulation channels. The results show that the ANN-based framework can playback the measured channels accurately, while GBSM-based simulated channels have large deviations. This work offers a solution to playback the measured channels accurately to be used in 5G and beyond radio system research and engineering applications, while it's also able to be applied in future channel predictions in case of large amount of measured data available.

W. Jiang and H. D. Schotten, “Deep learning for fading channel prediction”, 2020 channel state information (CSI), which enables wireless systems to adapt their transmission parameters to instantaneous channel conditions and consequently achieve great performance boost, plays an increasingly vital role in mobile communications. However, getting accurate CSI is challenging due mainly to rapid channel variation caused by multi-path fading. The inaccuracy of CSI imposes a severe impact on the performance of a wide range of adaptive wireless systems, highlighting the significance of channel prediction that can combat outdated CSI effectively. The aim of this article is to shed light on the state of the art in this field and then go beyond by proposing a novel predictor that leverages the strong time-series prediction capability of deep recurrent neural networks incorporating long short-term memory or gated recurrent unit. In addition to an analytical comparison of computational complexity, performance evaluation in terms of prediction accuracy is carried out upon multi-antenna fading channels. Numerical results reveal that deep learning brings a notable performance gain compared with the conventional predictors built on shallow recurrent neural networks.

T. Zhou, C. Tao, S. Salous, and L. Liu, “Geometry-based multi-link channel modeling for high-speed train communication networks”, 2020 the performance of distributed communication systems is commonly subject to the cross-correlation characteristics of multi-link channels. In this paper, we concentrate on the modeling of multi-link small-scale fading (SSF) channels in high-speed train (HST) communication networks with distributed base stations according to the classical geometry-based stochastic model (GBSM). To appropriately describe a multi-link propagation scenario in the HST communication network, a novel geometrical model considering a line-of-sight component, a single-bounced one-ring model, and a double-bounced ellipse-ring model is proposed. Based on the proposed GBSM, the expression of multi-link channel impulse responses (CIRs) is obtained, and multi-link cross-correlation functions are derived and used for numerical analysis. In addition, realistic channel measurements are conducted in the existing HST long-term evolution (LTE) networks and multi-link CIRs are acquired using a time delay window-based partitioning scheme. Finally, the SSF cross-correlation coefficient is extracted by the multi-link channel data and is used to validate the utility of the proposed model.

III. PROPOSED SYSTEM

A relay downlink communication system for HSR based on short packet is considered, where the relay device deployed on the top of the train provides communication services for multiple users in the carriage using DF mode. Downlink information transmission is divided into two phases. The first phase is the transmission from the base station to the relay device, and the second phase is the transmission from the relay device to the users. The sum of the blocklengths of the two phases is fixed. The contributions are mainly summarized as follows:

(1) Maximizing the throughput of the minimum user by jointly optimizing the blocklength and the transmission power of the relay device is studied, The constraints include the amount of data from the base station to the relay device is greater than that from the relay device to the user, the maximum blocklength, the minimum blocklength, and the transmit power of the on-board relay device.

(2) The formulated joint optimization problem is nonconvex, an alternate iteration algorithm is proposed in this paper. With fixed transmission power, the original optimization problem is transformed into an optimization subproblem about blocklength. Through variable substitution and the first-order Taylor expansion, the closed expression of blocklength can be obtained. By fixing the blocklength, the original problem is transformed into a non-convex optimization subproblem about transmission power. By introducing auxiliary variables and the first-order Taylor expansion, the non-convex optimization problem about transmission power is solved. On this basis, an alternate iteration algorithm for the joint optimization problem is proposed.

(3) The HSR relay communication system is simulated in detail, and the detailed simulation results are given to verify the effectiveness of the proposed algorithm. In addition, the simulation results also show the influence of the packetlength, the transmission power, the train speed and the channel error probability on the system transmission performance. 51446 V

The model of relay collaborative downlink system based on short-packet communication. It is assumed that there is an operator’s base station deployed at a certain distance from each other on the side of the HSR, and there is an on-board relay device deployed in each carriage of the train, which receives information from the roadside base station and serves multiple users in the carriage by DF. It is assumed that the base station, on-board relay device and subscriber are equipped with a single antenna. If the set of K users served in the compartment is denoted as K, where the user $k \in K = \{1, 2, \cdots, K\}.$ In order to ensure highly reliable and low latency communication, we use shortpacket communication, and the decoding error rate does not become zero even if the signal to interference plus noise ratio (SINR) is very high in this transmission, which leads to the Shannon formula no longer being applicable in this case. Let L^{max} denote the maximum channel block length, the downlink information transmission is divided into two phases. The first phase is the transmission phase from the base station to the vehicular relay device, and the second phase is the transmission phase from the vehicular relay device to the user. The corresponding block length of each stage are L^1 and L^2, respectively, and $L^1 + L^2 = L^{max}$. Under the finite channel blocklength constraint, the channel is considered as a quasi-static flat fading channel during transmission. In this paper, we only consider the joint optimization strategy design of block length and power allocation in short-packet transmission time period, so the system transmission model is quasistatic.

Let h_{vs} denote the channel gain from the base station to the on-board relay device and h_k denote the channel gain from the relay to the user k. The transmitting power of the base station and the transmitting power of the on-board relay device to user k are denoted as p_b and p_k , respectively. Then the SINR γ_{vs} and γk received by the relay and user k are expressed as follows,

$$\begin{cases} \gamma_{vs} = \dfrac{p_b h_{vs}}{p_b^{\prime} g_{vs} + \sigma_{vs}^{2\prime}} \\ \gamma_k = \dfrac{p_k h_h}{\sum_{l=1, l\neq k}^{k} p_l h_l + \sigma_k^{2\prime}} \end{cases}$$

where p_b' denotes the transmitting power of the adjacent base station, g_{vs} denotes the channel gain from the neighboring base station to the on-board relay device. σ_{vs}^2 and σ_k^2 denote the variance of AWGN.

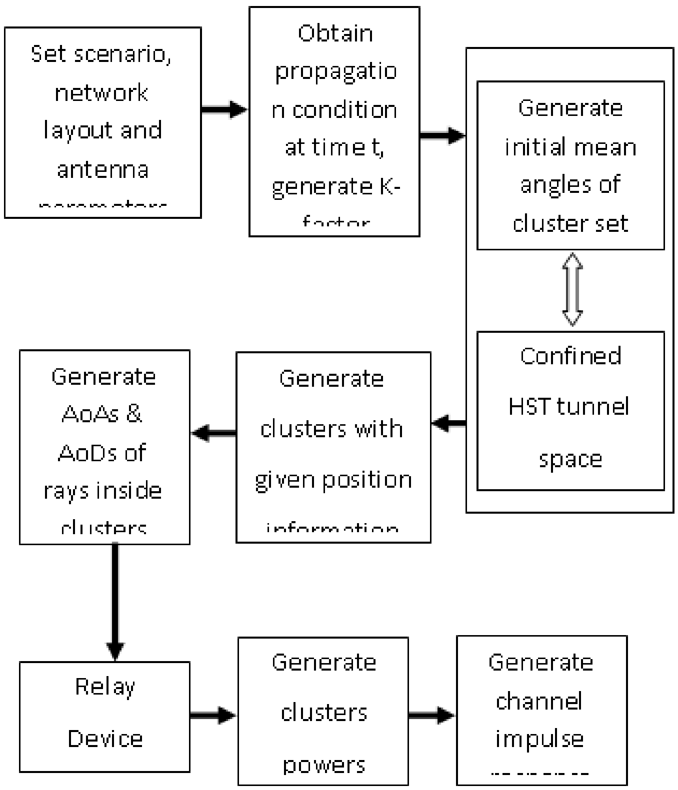


Fig.3.1 Proposed Block Diagram

In this method, a new formulation is used to portray the tradeoff between achievable rate of data transmission, decoding error probability and transmission delay under the transmission condition of shorter block length. For a given finite block length L^{max} ($L^{max} < 100$), the channel decoding rate can be described by,

$$R(L^{max}, \epsilon) = C - \sqrt{\frac{V}{L^{max}}} Q^{-1}(\epsilon) + O\left(\frac{\log L^{max}}{L^{max}}\right)$$

where C is based on the Shannon capacity at infinite blocklength, V denotes the channel discretization, which measures the randomness of the channel relative to a deterministic channel with the same capacity, ϵ denotes the expected decoding error probability, and Q^{-1} is the inverse function of the Gaussian Q-function,

$$Q(x) \triangleq \int_x^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$$

According to the above equation, the approximate decoding rates R (γ_{vs}) and R (γ_k) of the information received by the on-board relay device and user k can be obtained as follows

$$\begin{cases} R(\gamma_{vs}) = \log_2(1+\gamma_{vs}) - \sqrt{\dfrac{V(\gamma_{vs})}{L_1}} \dfrac{Q^{-1}(\varepsilon_{vs})}{ln2} \\ R(\gamma_k) = \log_2(1+\gamma_k) - \sqrt{\dfrac{V(\gamma_k)}{L_2}} \dfrac{Q^{-1}(\varepsilon_k)}{ln2} \end{cases}$$

Where

$(\gamma_{vs}) = (1-(1+\gamma_{vs})^{-2})(\log_2 e)^2, V(\gamma_{vs}), \; V(\gamma_k) = (1-(1+\gamma_{vs})^{-2})(\log_2 e)^2.$

Obviously, this approximation adds a rate penalty term compared with the channel capacity to keep the maximum channel error probability ε at a finite block length L^{max}, which is proportional to $\frac{1}{\sqrt{L^{max}}}$. ε_{vs} denotes the maximum channel error probability from the base station to the on-board relay, and ε_k denotes the maximum channel error probability from the on-board relay to the user.

Here maximize the throughput of the minimum user by jointly optimizing the block length and power, and the specific optimization problem is expressed as follows,

$$P: \max_{L_1, L_2, P_k} \min_{k \epsilon K} L_2(1-\varepsilon_k) R(\gamma_k)$$

$$L_1(1-\varepsilon_{vs}) R(\gamma_{vs}) \geq L_2 \sum_{k=1}^{K} (1-\varepsilon_k) R(\gamma_k)$$

$$L_1 + L_2 = L^{max},$$

$$L_1 \geq L^{min}, L_2 \geq L^{min}, L_1, L_2 \in N,$$

$$0 \leq \sum_{k=1}^{K} P_k \leq P^{max} \; k \in K$$

The constraint is to ensure that the data from the base station to the on-board relay device in the first phase can all be decoded and forwarded to the user in the relay in the second phase. The constraint ensures that the block length of the two phases is equal to the maximum block length. The constraint ensures that the minimum block length L min is satisfied in each phase, and constraint is the transmit power constraint of the on-board relay device. The problem P is a nonconvex optimization problem, which is solved by the alternating iterative method.

FIXED TRANSMISSION POWER TO OPTIMIZE BLOCKLENGTH

By fixing the transmitting power p_k , k ∈ K, the problem P is transformed into an optimization problem with respect to the block lengths L_1, L_2 as follows,

$$P:\max_{L_1,L_2}\min_{k\epsilon K}\Delta_k L_2-\ \Delta_k L_2^{1/2}$$

$$\varphi_{vs}L_1-\Psi_{vs}L_1^{1/2}\geq\sum_{k=1}^{K}\left(\Delta_k L_2-\ \Delta_k L_2^{\frac{1}{2}}\right)$$

$$L_1+L_2=L^{max}$$

$$L_1\geq L^{min},L_2\geq L^{min},L_1,L_2\ \in N,$$

$$\max_{L_2}\min_{k\epsilon K}\Delta_k L_2-\ \Delta_k L_2^{1/2}$$

$$(\varphi_{vs}+\Delta)L_2-\wedge L_2^{\frac{1}{2}}+\Psi_{vs}(L^{max}-L_2)^{1/2}\leq\varphi_{vs}L^{max}$$

$$L^{min}\leq L_2\leq L^{max},L_2\ \in N,$$

Since the constraints are both nonconvex, by calculating the first-order Taylor expansions of $\Psi_{vs}(L^{max}-L_2)^{1/2}$ and $-\Delta_k L_2^{1/2}$ at the feasible point L_2^t , the upper and lower bounds at the feasible point L_2^t can be obtained, respectively,

Since the constraints are both nonconvex, by calculating the first-order Taylor expansions of $\Psi_{vs}(L^{max}-L_2)^{1/2}$ and $-\Delta_k L_2^{1/2}$ at the feasible point L_2^t , the upper and lower bounds at the feasible point L_2^t can be obtained, respectively,

$$\begin{cases}\Psi_{vs}(L^{max}-L_2)^{\frac{1}{2}}\leq\Psi_{vs}(L^{max}-L_2^t)^{\frac{1}{2}}-\frac{1}{2}\Psi_{vs}(L^{max}-L_2^t)^{1/2}\\ -\Lambda_k L_2^{\frac{1}{2}}\geq-\Lambda_k(L_2^t)^{1/2}-\frac{1}{2}\Lambda_k(L_2^t)^{-1/2}(L_2-L_2^t)\end{cases}$$

By fixing the block lengths L_1, L_2, the problem P is transformed into an optimization problem on the transmitting power p_k , k ∈ K, as follows,

$$\max_{p_k}\min_{k\epsilon K}L_2(1-\varepsilon_k)\,R(\gamma_k)$$

$$L_1(1-\varepsilon_{vs})\,R(\gamma_{vs})\geq L_2\sum_{k=1}^{K}(1-\varepsilon_k)\,R(\gamma_k)$$

$$0\leq\sum_{k=1}^{K}P_k\leq P^{max}\ k\in K$$

By introducing the variable ρ, ψ_k , ϕ_k , k ∈ K, problem P2 is transformed into the following equivalent problem,

$$\max_{p_k,\psi k,\phi k}\rho$$

$$L_1(1-\varepsilon_{vs})\,R(\gamma_{vs})\geq L_2\sum_{k=1}^{K}(1-\varepsilon_k)\,R(\gamma_k,\psi_k)$$

$$L_2(1-\varepsilon_k)R(\gamma_k,\phi_k)\geq\rho,$$

$$\frac{p_k h_k}{\sum_{l=1,l\neq k}^{K}p_l h_l+\sigma_k^2}\geq\psi k,k\ \in\ K$$

$$\frac{p_k h_k}{\sum_{l=1,l\neq k}^{K}p_l h_l+\sigma_k^2}\geq\phi_k,k\ \in\ K$$

$$0\leq\sum_{k=1}^{K}p_k\leq P^{max}\ k\in K$$

The constraints are all nonconvex. We will deal with them separately and convert them into the form of convex constraints. For constraint $L_2(1-\varepsilon_k)R(\gamma_k,\psi_k)$ can be written in the following form,

$$L_2(1-\varepsilon_k)R(\gamma_k,\psi_k) = L_2(1-\varepsilon_k)\log_2\sum_{l=1}^{K} p_l h_l + \sigma_k^2$$

$$-L_2(1-\varepsilon_k)\log_2\sum_{l=1,l\neq k}^{K} p_l h_l + \sigma_k^2 -$$

$$-L_2^{1/2}(1-\varepsilon_k)\sqrt{1-(1+\psi k)^{-2}}\,\frac{Q^{-1}(\varepsilon_{vs})}{ln2}$$

In the above equation, where $\log_2(\sum_{l=1}^{K} p_l h_l + \sigma_k^2)$ is a concave function, its first-order Taylor expansion at the feasible point p_l^t, l ∈ K yields the upper bound as follows,

$$\log_2(\sum_{l=1}^{K} p_l h_l + \sigma_k^2) \le \log_2\left(\sum_{l=1}^{K} p_l^t h_l + \sigma_k^2\right) + \sum_{l=1}^{K}\frac{h_l(p_l - p_l^t)}{ln2(\sum_{l=1}^{K} p_l^t h_l + \sigma_k^2}$$

$$A = L_1(1-\varepsilon_{vs})R(\gamma_{vs}) - \sum_{k=1}^{K}(L_2(1-\varepsilon_k)(\log_2(\sum_{l=1}^{K} p_l^t h_l + \sigma_k^2)$$

$$-\sum_{l=1}^{K}\frac{h_l p_l^t}{ln2(\sum_{l=1}^{K} p_l^t h_l + \sigma_k^2}$$

$$B_k = L_2(1-\varepsilon_k)$$

$$C_k = L_2^{1/2}(1-\varepsilon_k)\,\frac{Q^{-1}(\varepsilon_k)}{ln2}$$

$$D_{k,l} = \frac{h_l}{ln2(\sum_{l=1}^{K} p_l^t h_l + \sigma_k^2}$$

$$\sum_{l=1}^{K} B_k \sum_{l=1}^{K} D_{k,l} p_l - \sum_{k=1}^{K} B_k \log_2(\sum_{l=1,l\neq k}^{K} p_l h_l + \sigma_k^2)) - \sum_{K=1}^{K} C_k\sqrt{1-(1+\psi k)^{-2}} \le A$$

$$L_2(1-\varepsilon_k)R(\gamma_k,\phi_k) = L_2(1-\varepsilon_k)\log_2\sum_{l=1}^{K} p_l h_l + \sigma_k^2$$

$$-L_2(1-\varepsilon_k)\log_2\sum_{l=1,l\neq k}^{K} p_l h_l + \sigma_k^2 -$$

$$-L_2^{1/2}(1-\varepsilon_k)\sqrt{1-(1+\phi k)^{-2}}\,\frac{Q^{-1}(\varepsilon_k)}{ln2}$$

In the above equation, $-\log_2(\sum_{l=1,l\neq k}^{K} p_l h_l + \sigma_k^2)$ is convex function. Calculate its first-order Taylor expansion at the feasible point p_l^t, l ∈ K and yield the following lower bound,

$$-\log_2(\sum_{l=1,l\neq k}^{K} p_l h_l + \sigma_k^2) \ge \log_2\left(\sum_{l=1\,l\neq k}^{K} p_l^t h_l + \sigma_k^2\right) - \sum_{l=1,l\neq k}^{K}\frac{h_l}{ln2(\sum_{l=1\,l\neq k}^{K} p_l^t h_l + \sigma_k^2}(p_l - p_l^t)$$

IV. RESULT AND DISCUSSION

4.1 SYMBOL CONSTELLATION

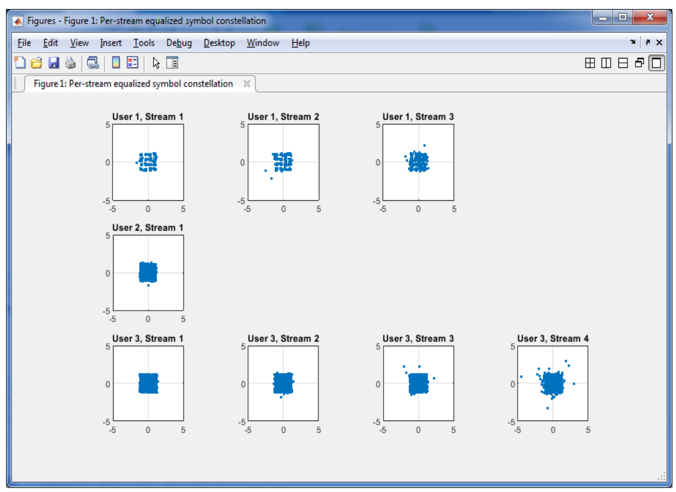


Fig 4.1 Symbol Constellation

4.2 DIPOLE PATTERN PLOTS

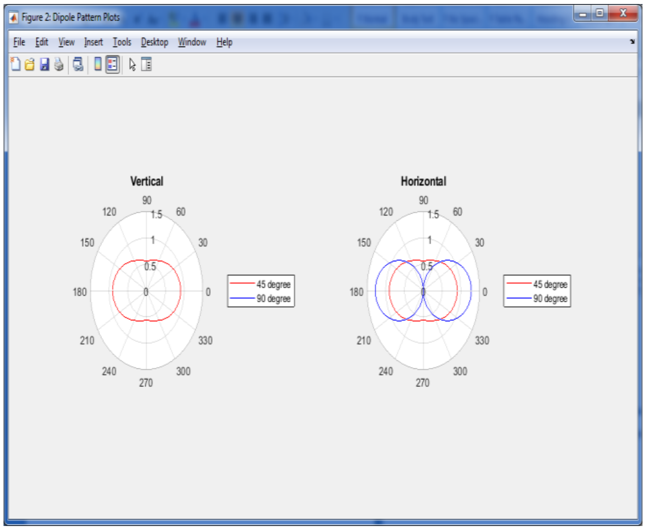


Fig 4.2 Dipole Pattern Plots

4.3 POSITION PLOT FOR STATIONS

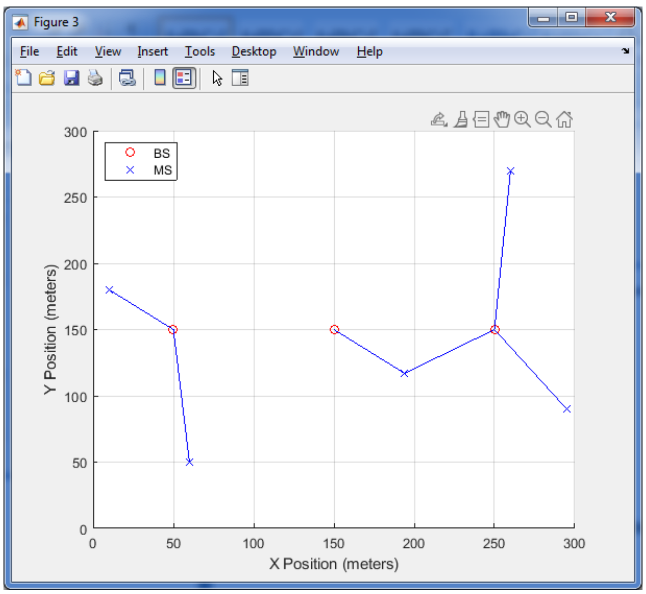
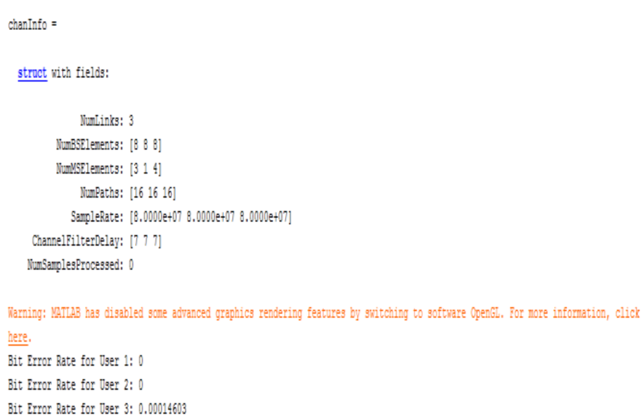


Fig 4.3 Position Plot for Stations

4.4 BER PERFORMANCE WINDOW



```
chanInfo =

  struct with fields:

          NumLinks: 3
      NumBSElements: [8 8 8]
      NumMSElements: [3 1 4]
          NumPaths: [16 16 16]
        SampleRate: [8.0000e+07 8.0000e+07 8.0000e+07]
  ChannelFilterDelay: [7 7 7]
 NumSamplesProcessed: 0

Warning: MATLAB has disabled some advanced graphics rendering features by switching to software OpenGL. For more information, click here.
Bit Error Rate for User 1: 0
Bit Error Rate for User 2: 0
Bit Error Rate for User 3: 0.00014603
```

Fig 4.4 BER Performance Window

4.5 TRANSMITTING POWER, THE RELATIONSHIP BETWEEN THE RECEIVED DATA AND THE DATA BLOCK LENGTH

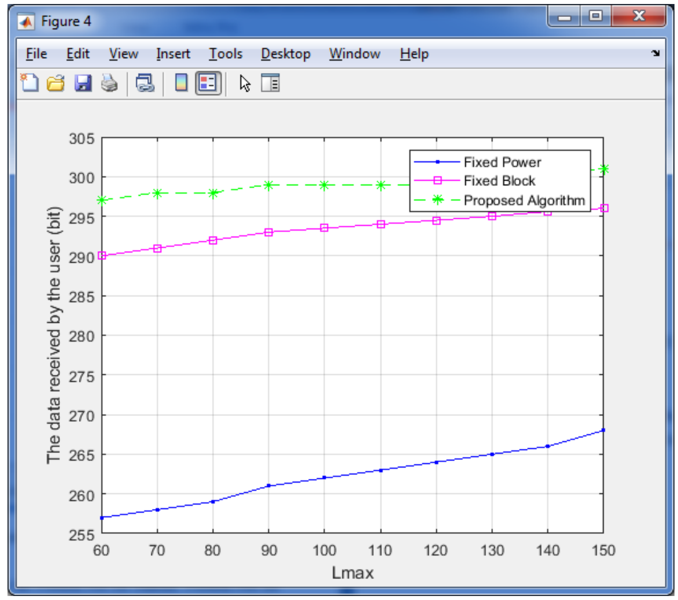


Figure 4.5 Transmitting power, the relationship between the received data and the data block length

4.6 DATA BLOCKLENGTH, THE RELATIONSHIP BETWEEN THE RECEIVED DATA AND THE TRANSMITTING POWER OF THE RELAY NODE

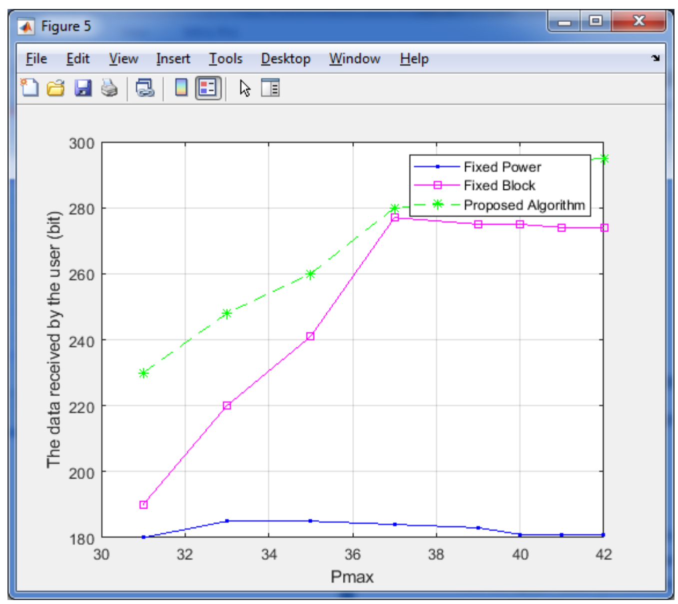


Figure 4.6 Data block length, the relationship between the received data and the transmitting power of the relay node

4.7 DATA BLOCK LENGTH AND THE TRANSMITTING POWER OF THE ON-BOARD RELAY DEVICE, THE RELATIONSHIP BETWEEN THE RECEIVED DATA AND DRIVING SPEED

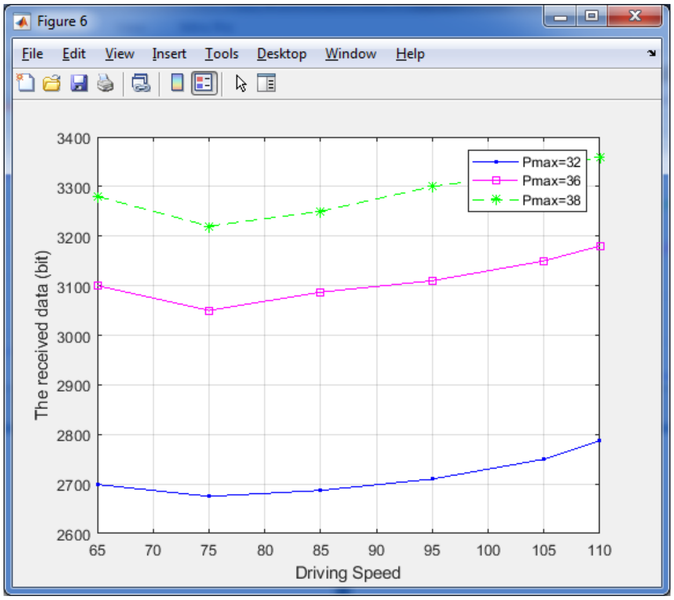


Figure 4.7 Data block length and the transmitting power of the on-board relay device, the relationship between the received data and driving speed.

V. CONCLUSION

A relay downlink system for HSR communication based on short-packet transmission, and studied the optimization problem of maximizing the minimum user throughput under the constraints of transmission blocklength and transmitting power of relay device. The formed optimization problem was nonconvex, and two optimization sub problems were solved by fixing one variable and solving the other variable. Based on solving the sub problems, an alternating iteration algorithm was proposed. Finally, the effectiveness of the proposed algorithm was verified by simulation. In the next step of research, the effect of multiple relay node diversity or collaboration on the system performance will be considered.

REFERENCES

[1] Duel-Hallen, "Fading channel prediction for mobile radio adaptive transmission systems," Proc. IEEE, vol. 95, no. 12, pp. 2299–2313, Dec. 2007.

[2] Ai, A. F. Molisch, M. Rupp, and Z.-D. Zhong, "5G key technologies for smart railways," Proc. IEEE, vol. 108, no. 6, pp. 856–893, Jun. 2020.

[3] Xue, T. Zhou, H. Zhang, L. Liu, and C. Tao, "Deep learning based channel prediction for massive MIMO systems in high-speed railway scenarios," in Proc. IEEE 93rd Veh. Technol. Conf. (VTC-Spring), Helsinki, Finland, Apr. 2021, pp. 1–5.

[4] Wu, G. Zhu, and B. Ai, "Application of artificial neural networks for path loss prediction in railway environments," in Proc. 5th Int. ICST Conf. Commun. Netw. China, Beijing, China, 2010, pp. 1–5.

[5] Ostlin, H.-J. Zepernick, and H. Suzuki, "Macrocell path-loss prediction using artificial neural networks," IEEE Trans. Veh. Technol., vol. 59, no. 6, pp. 2735–2747, Jul. 2010.

[6] Hasegawa et al., "High-speed train communications standardization in 3 GPP 5G NR," IEEE Commun. Standards Mag., vol. 2, no. 1, pp. 44–52, Mar. 2018.

[7] J. Hoydis, F. A. Aoudia, A. Valcarce, and H. Viswanathan, "Toward a 6G AI-native air interface," IEEE Commun. Mag., vol. 59, no. 5, pp. 76–81, May 2021.

[8] J. Huang, C. X. Wang, L. Bai, J. Sun, and Y. Yang, "A big data enabled channel model for 5G wireless communication systems," IEEE Trans. Big Data, vol. 6, no. 2, pp. 211–222, Jun. 2020.

[9] J. Zhang, Y. Zheng, D. Qi, R. Li, and X. Yi, "DNN-based prediction model for spatial-temporal data," in Proc. ACM SIGSPATIAL Interface Conf. Adv. Geo. Infor. Sys., Los Angeles, CA, USA, 2016, pp. 1–4.

[10] J.-Y. Wu and W.-M. Lee, "Optimal linear channel prediction for LTE-A uplink under channel estimation errors," IEEE Trans. Veh. Technol., vol. 62, no. 8, pp. 4135–4142, Oct. 2013.

[11] L. Bai et al., "Predicting wireless mmWave massive MIMO channel characteristics using machine learning algorithms," Wireless Commun. Mobile Comput., vol. 2018, pp. 1–12, Aug. 2018.

[12] R. Chen, W.-X. Long, G. Mao, and C. Li, "Development trends of mobile communication systems for railways," IEEE Commun. Surveys Tuts., vol. 20, no. 4, pp. 3131–3141, Jul. 2018.

[13] R. Li et al., "Intelligent 5G: When cellular networks meet artificial intelligence," IEEE Wireless Commun., vol. 24, no. 5, pp. 175–183, Oct. 2017.

[14] R. O. Adeogun, P. D. Teal, and P. A. Dmochowski, "Parametric channel prediction for narrowband mobile MIMO systems using spatio-temporal correlation analysis," in Proc. IEEE 78th Veh. Technol. Conf. (VTC Fall), Las Vegas, NV, USA, Sep. 2013, pp. 1–5.

[15] S. Lin, Y. Jia, and S. Xia, "Research and analysis on the top design of smart railway," J. Phys., Conf. Ser., vol. 1187, no. 5, pp. 1–7, Apr. 2019.

[16] S. Xingjian, Z. Chen, H. Wang, D.-Y. Yeung, W.-K. Wong, and W.-C. Woo, "Convolutional LSTM network: A machine learning approach for precipitation nowcasting," in Proc. Adv. Neural Inf. Process. Syst., Montreal, QC, Canada, 2015, pp. 802–810.

[17] T. Ding and A. Hirose, "Fading channel prediction based on combination of complex-valued neural networks and

chirp Z-transform," IEEE Trans. Neural Netw. Learn. Syst., vol. 25, no. 9, pp. 1686–1695, Sep. 2014.
[18] W. Jiang and H. D. Schotten, "A comparison of wireless channel predictors: Artificial intelligence versus Kalman filter," in Proc. IEEE Int. Conf. Commun. (ICC), Shanghai, China, May 2019, pp. 1–6.
[19] W. Jiang and H. D. Schotten, "Deep learning for fading channel prediction," IEEE Open J. Commun. Soc., vol. 1, pp. 320–332, 2020.
[20] W. Jiang and H. D. Schotten, "Neural network-based fading channel prediction: A comprehensive overview," IEEE Access, vol. 7, pp. 118112–118124, 2019.
[21] W. Jiang and H. D. Schotten, "Recurrent neural network-based frequency-domain channel prediction for wideband communications," in Proc. IEEE 89th Veh. Technol. Conf. (VTC-Spring), Kuala Lumpur, Malaysia, Apr. 2019, pp. 1–6.
[22] X. Zhao et al., "Playback of 5G and beyond measured MIMO channels by an ANN-based modeling and simulation framework," IEEE J. Sel. Areas Commun., vol. 38, no. 9, pp. 1945–1954, Sep. 2020.
[23] Y. Chen, Z. Dou, Y. Lin, and Y. Li, "Prediction of V2V channel quality under double-Rayleigh fading channels," in Proc. IEEE 91st Veh. Technol. Conf. (VTC-Spring), Antwerp, Belgium, May 2020, pp. 1–6.
[24] Y. Zhang, J. Wen, G. Yang, Z. He, and X. Luo, "Air-to-air path loss prediction based on machine learning methods in urban environments," Wireless Commun. Mobile Comput., vol. 2018, pp. 1–9, Jun. 2018.