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An Improved Interference Alignment Algorithm With User Mobility Prediction for High-Speed Railway Wireless Communication Networks

JIE SHENG^{1,2}, ZIWEN TANG², QIAOMING ZHU¹, CHENG WU^{1,2} (Member, IEEE),
YIMING WANG^{1,2} (Senior Member, IEEE), AND BO AI^{1,3} (Senior Member, IEEE)

¹School of Computer Science and Technology, Soochow University, Suzhou 215011, China

²School of Rail Transportation, Soochow University, Suzhou 215011, China

³State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing 100044, China

Corresponding authors: Qiaoming Zhu (qmzhu@suda.edu.cn) and Cheng Wu (cwu@suda.edu.cn)

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ABSTRACT The enhancement of the carrying capacity of high-speed railway and the acceleration of train speed lead to the proliferation of signal interference in the communication network, which leads to the degradation of network performance and user service quality. To address the issue, we first classify the cell users in high-speed railway wireless communication environment based on Fuzzy C-Means algorithm and user mobility prediction model, and divide communicating users on trains into cell center users and edge users. Then, differential power distribution schemes are implemented for center users and edge users according to the classification results. Finally, the Max-SINR based interference alignment algorithm is used to realize the interference management. Simulation results show that the proposed algorithm fully takes into account the mobility of high-speed train users and effectively manages interference, which improves the high-speed railway wireless communication network performance significantly.

INDEX TERMS High-speed railway communication, interference alignment, mobility prediction, fuzzy C-means, user classification.

I. INTRODUCTION

In recent years, the construction scale and operation speed of high-speed railway (*HSR*) have been rapidly developed. Combined with the upcoming deployment of the Fifth generation (*5G*) communication system, the *HSR* wireless communication network architecture will gradually transform from the traditional cellular network to the heterogeneous cellular network (*HCN*) [1]–[4]. However, the huge increase of the base station deployment density as well as the improvement of the train speed make the interference management of the railway communication system more difficult, and bring about the decline of the communication quality of train users. In *5G* ultra-dense network (*UDN*)-oriented *HSR* communication, interference is mainly caused by the reduction of the distance between cells resulted from large-scale deployment of base stations (*BSes*) [5]–[7]. A large number of studies

have confirmed that with the increase of the density of *BSes*, communication links and the complexity of the network level as well, the signal interference becomes more and more serious, and the signal-to-noise ratio (*SNR*) as well as the average speed of users can not reach the ideal value [8], [9]. In order to improve network performance and meet the demand of network quality of service for wireless mobile users, *5G* heterogeneous ultra dense network (*H-UDN*) oriented to *HSR* system should be fully considering the interference caused by the time-varying environment and user mobility, and the interference management solutions should be adopted, so that the utilization of the wireless resources can be improved and the quality of various services can be guaranteed.

Interference Alignment (*IA*) is an efficient interference management technology. It uses the compression of interference space dimensions and the amplification of desired signal space dimensions to realize the effective separation of interference signal and the desired signal at the receiving end, as well as increase the channel capacity and reliability of

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wireless communication system. The technology is becoming one of the key technologies of public communication system [10]–[14]. In the *HSR* communication environment, the train runs along the track, and the wireless communication users on the train continuously drive from the edge of a chain-distributed BS cell to its center, and from the center to the edge of the cell. Therefore, the channel quality of the users on the train changes constantly. The channel quality of cell center users is relatively good while the channel quality of edge users is not optimistic. As a result, in order to improve the network performance of the center users and meet the service quality requirements of the edge users, it is necessary to make a reasonable distinction between the edge users and the central users in the high-speed rail communication networks according to the prediction of user mobility, and the adaptive resource management and interference elimination strategies should be adopted for the users with different types.

In terms of the user classification, the current research is mainly focus on setting a fixed threshold according to one or several performance criteria of the users, and those who are better than the threshold are judged as cell center users, while those who are worse than the threshold are judged as cell edge users. The advantage of the algorithm is simple and easy to implement, but it is often unable to maximize the efficiency of the system because it only considers one or a few performance indexes. In addition, the user mobility is not fully considered in the classical algorithm which has definitely a great impact on the change of the users type in the *HSR* communication environment.

The fuzzy theory focuses on the fuzziness of the set and adopts the membership function to describe the degree to which things belong to different sets. The membership function is between 0 and 1, and the closer it is to 1, the higher the degree to which the object belongs to the set. In user classification, the judgment of whether the user belongs to the center user or the edge user has relativity and fuzziness. Therefore, it is more suitable to apply the fuzzy theory than the set determination method for non-zero or one in user classification. Some studies have used power allocation techniques in interference-aligned radio networks to improve network performance [15]. Applying user classification results to power allocation algorithm can improve the effect of IA, effectively suppress the interference signals of classified users, and improve the overall performance of the system. Based on the analysis above, we are committed to research an mobile user classification based IA algorithm for the *HSR* wireless communication networks in the article.

The structure of this article is organized as follows. Section II outlines the works of the existing IA and user classification algorithms. In the Section III, we set up a *HSR* communication system model and propose a novel user classification algorithm based on the prediction of train user mobility. On this basis, we also study an improved interference alignment algorithm. The simulation environment description, network parameter settings, and the experimental results and analysis are given in the Section IV. Finally,

Section V summarizes the article and discusses some of future work.

II. RELATED WORK

In the *HSR* scenarios, the design of the network architecture is particularly important due to the Doppler frequency shift, the severe carriage penetration loss, the complex channel environment and the “signaling storm” caused by group handover. The dual-hop network architecture based on the on-board relay has installed the train relay station(*TRS*) on the top of the train [16]. The user equipment(*UE*) can be connected to the *TRS* through the access points(*AP*) deployed in the carriages, which can effectively reduce the transmission loss of the carriage, improve the quality of the received signals, and save the energy of the user terminal. In order to improve the handover success rate and the system stability, Tian *et al.* proposed a dual-antenna scheme based on the *TRS*, in which the two antennas were installed as the train relay stations at the front and the rear of the train respectively [17], [18]. However, this dual-hop network architecture with added relays increases end-to-end delay, has the risk of “all-or-none” group handover, and needs to achieve the integration problems with the train control systems [1]. On the other hand, the traditional cellular systems for high-speed trains support the interactive mode of direct communication between the passengers and the BSes [1]. With the large-scale construction of the 4G and 5G BSes and the maturity of MIMO technology, the public mobile communication network can meet the real-time communication requirements of the high-speed mobile, massive and mass data services. A growing number of *HSR* passengers are wirelessly connecting their mobile terminals such as mobile phones and tablets that support the cellular communications with the public mobile communication BSes and accessing the Internet. The interference alignment method studied in this paper is based on this single-hop communication network architecture.

In recent years, due to the feasibility and effectiveness, IA has attracted many scholars to study this field. The current researches focus on various IA algorithms in the ideal and non-ideal channels, combined with power allocation [19]–[21]. Many scholars believe that the IA combined with power allocation is more effective in considering the resource allocation of the network system, which makes power allocation-based IA to become one of the research hotspots. It is critical to consider both the time-varying channel state information (*CSI*) and the reasonable power allocation to the user. On the one hand, scholars dynamically calculate the precoding matrix and power allocation according to the time-varying channel matrix, as in [15], [19]. On the other hand, game theory is used to maximize the system performance to calculate the power allocation, such as [20], [21]. Literature [20] is a representative study for dynamic power allocation. For the case of *CSI* with delay and error, a joint interference phase alignment algorithm based on Bayesian estimation and inter-stream power allocation for

multi-cell Multiuser MIMO broadcast channels (MIMO-BC) is proposed. In [21], in order to improve the transmission rate of cognitive radio MIMO (CR-MIMO) systems, a game-theory-based IA algorithm is proposed. The algorithm uses the water-flood algorithm to allocate power to the primary user, and designs the secondary users precoding so that their signals fall into the sub-channel of the unassigned power of the primary user, then the multiple interference links between the different users constitute a game. The model is solved to achieve efficient IA between secondary users. However, there are not many verification algorithms for high-speed movement in UDNs. Furthermore, the existing methods lack of the consideration of the classification of mobile users. It is necessary to carry out some reasonable power distribution and interference management strategies according to the user classification results.

In terms of user classification, many scholars believe that user classification is the basis of improving communication quality and system resource allocation. The existing user classification algorithm is mainly designed based on three indicators, including the distance between user and BSes, the signal to interference plus noise ratio ($SINR$) received by the user and the reference signal receiving power (RSRP) [22]–[24]. Czerwinski *et al.* set the threshold of distance between the user and the BS in literature [22]. If the distance is greater than this threshold, the user is judged to be an edge user, otherwise a center user. $SINR$ can reflect better the interference situation and signal quality of users, and be an important indicator to evaluate channel state. Therefore, Novlan *et al.* set a rational threshold value of the $SINR$ to distinguish user categories according to experience in literature [23]. If the received $SINR$ of the user is greater than this threshold, the user is the center user; otherwise, the user is the edge user. In literature [24], a RSRP double threshold escalation mechanism based user classification method was presented by Qi *et al.* This method sets the upper limit and the lower limit of RSRP, and sets a transition zone between the upper limit and the lower limit for user type discrimination. In this way, even if the user is in the channel with drastic changes in performance, the user category would not be changed frequently, effectively reducing the waste of network resources.

However, the factors that affect the channel qualities of users are multiple, and the classification of users by only one attribute tends to be one-sided. Hence, some researchers put forward the use of multiple attributes to make user classifications. Based on the fuzzy C-means (FCM) theory, Cai and Yan [25] presented an improved granulation feature weighted multi-label classification algorithm. The algorithm granulates the label space, calculates the membership degree of each feature parameter to the labelled particles and their correlation by information gain, and determines the weight coefficient of the feature for weighting, thus determining the user category. The algorithm solves the problem of the correlation between the features and the labels and the explosion of the tag combination, and achieves good results in the

evaluation index. In Literature [26], Zhan designed a two-attributes based classification algorithm. The algorithm divides the users into three categories according to their distances to the BS, and then types the users with medium distance according to the value of $SINR$. Finally, the classification results are used for interference management of the system by the interference coordination algorithm, which greatly improves the $SINR$ of the central user and the total throughput of the system. In the *HSR* scenario, the high-speed mobility of trains has a great impact on the accuracy of classifying of user categories, so the user classification algorithm needs to consider the mobility prediction problem. In Literature [27], Lin *et al.* proposed a Markov location prediction algorithm based on user mobile behavior similarity clustering, which can help solve the user classification problem requiring mobility prediction in *HSR* scenarios.

It can be seen that there are many user classification algorithms, and various algorithms have their own characteristics in solving practical problems. However, there are not many studies and discussions on the communication quality of users in *HSR* communication system. Therefore, there are still some problems worthy of our consideration and discussion. Firstly, how to determine the edge users based on the location prediction of the mobile users reasonably in railway wireless communication system. Secondly, how to solve the problem of channel quality degradation caused by high-speed mobility in railway wireless communication. With the above questions and research objectives, this article will carry out the research on the IA algorithm considering user classification in *HSR* environment.

III. METHODOLOGY

A. SYSTEM MODEL

In the *HSR* environment, the wireless BSes are generally deployed along the railway track in a strip. With the development of wireless communication in recent years, the types of BSes distributed on both sides of the orbit are more diversified, including GSM-R, LTE-R and 5G BSes. We consider the single-hop communication between the on-board passengers and the BSes, and the train will pass through the heterogeneous network covered by these BSes at a faster speed, as shown in Figure 1. In the above scenario, the user on the train will enter the boundary of the cell at a fast speed, cross the central area of the cell, reach the boundary of the cell again, and then cross to the next base station coverage area. In this process, the Doppler Effect caused by the rapid movement will cause the signal quality of the users to be in the instantaneous random fluctuation state, thus affecting the communication service quality of the users on the train. For the BS, as the train moves quickly into its coverage area, there will be a surge in the number of users, which will have an impact on network performance. Therefore, the BS needs to be sensitive to distinguish the user types and provide differentiated services to different users to ensure the QoS for each user.

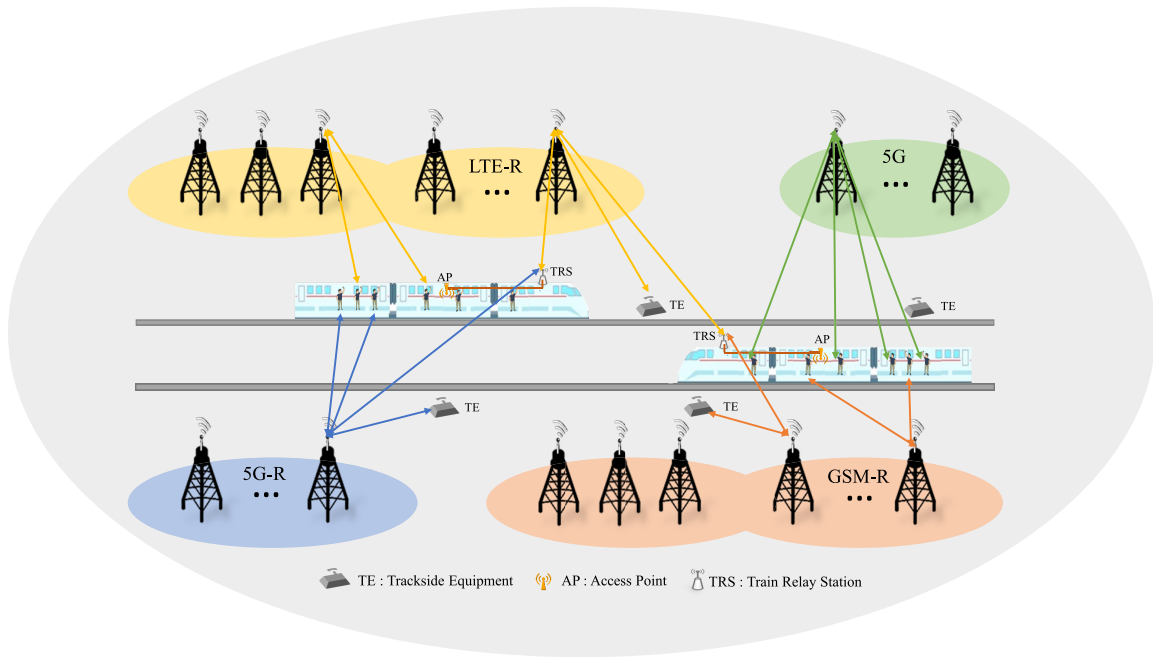


FIGURE 1. The scenario of High-speed railway wireless communication networks.

B. FUZZIFICATION OF MOBILE USERS LOCATION ATTRIBUTES

In the HSR environment, the location of mobile users relative to the BS has strong real-time performance, which needs to be considered from multiple aspects. Thus, we take into account three attributes: the distance from User i to the serving BS BS_c , denoted as $d_i^{BS_c}$, the distance from User i to the next BS, denoted as $d_i^{BS_{next}}$, and the $SINR$ of the received signals.

In the process of discretization of continuous data, the traditional algorithm generally divides the continuous value domain into several discrete value intervals by setting several discrete thresholds, and defines a certain output value in each interval as the quantization result, which often leads to a large quantization error. The fuzzy c -means (FCM) clustering algorithm [12] can obtain the membership degree of each sample point to all centers by optimizing the objective function, so as to determine the category of sample points and automatically classify the sample data, which is more objective, reasonable and scientific. Therefore, we use the FCM clustering algorithm for fuzzy processing of the continuous attributes including $d_i^{BS_c}$ and $SINR$ in the paper.

According to the FCM clustering method, we first need to determine the objective function to be optimized, and then achieve user classification by minimizing the objective function. Using the membership degree U to indicate how much the user belongs to a certain type. The fuzzy C partitioning objective function of user space is $X = x_1, x_2, \dots, x_M$. The objective function of FCM is defined as shown in Equation (1).

$$J = \sum_{j=1}^c \sum_{i=1}^M (\mu_{ij})^m l_{ij}^2, \quad 1 \leq m \leq \infty \quad (1)$$

where c represents the number of user categories, and M represents the number of users. μ_{ij} represents the degree to which the i -th user belongs to the j -th category, $\mu_{ij} \in [0, 1]$, and the higher the value, the more inclined user i is to type j . x_i represents the attribute of user i . z_j represents the cluster center of type j . In addition, $l_{ij} = \|x_i - z_j\|$ represents the Euclidean distance between user i and the clustering center z_j , and m represents the fuzzy weight corresponding to the function. The membership of each user in a different category adds up to 1.

$$\sum_{j=1}^c \mu_{ij} = 1, \quad i = 1, 2, \dots, M \quad (2)$$

Construct a new objective function as follows to get the necessary conditions of approaching the minimum value obtained by the objective function:

$$\begin{aligned} J(U, z_1, \dots, z_c, \lambda_1, \dots, \lambda_M) &= J(U, z_1, \dots, z_c) + \sum_{i=1}^M \lambda_i (\sum_{j=1}^c \mu_{ij} - 1) \\ &= \sum_{j=1}^c \sum_{i=1}^M \mu_{ij}^m l_{ij}^2 + \sum_{i=1}^M \lambda_i (\sum_{j=1}^c \mu_{ij} - 1) \end{aligned} \quad (3)$$

where $\lambda_i = (i = 1, \dots, M)$ is M constrained Lagrangian multipliers. According to the requirements of the Equation (2), we are seeking for the minimum value obtained by the objective function. We set the partial derivative of z_j and μ_{ij} equal to 0, and connect it with the solutions of Equation (1) and (3), we can get the clustering centers as shown in Equation (4):

$$z_j = (\sum_{i=1}^M \mu_{ij}^m x_i) (\sum_{i=1}^M \mu_{ij}^m)^{-1}, \quad j = 1, 2, 3, \dots, c \quad (4)$$

TABLE 1. User classification decision based on fuzzy attributes.

	$d_i^{BS_c}$			$d_i^{BS_{n,ext}}$			SINR			Decision
user ₁	w ₁	μ ₁₁	q ₁₁	w ₂	μ ₁₂	q ₁₂	w ₃	μ ₁₃	q ₁₃	D ₁
user ₂	w ₁	μ ₂₁	q ₂₁	w ₂	μ ₂₂	q ₂₂	w ₃	μ ₂₃	q ₂₃	D ₂
user ₃	w ₁	μ ₃₁	q ₃₁	w ₂	μ ₃₂	q ₃₂	w ₃	μ ₃₃	q ₃₃	D ₃
...
user _M	w ₁	μ _{M1}	q _{M1}	w ₂	μ _{M2}	q _{M2}	w ₃	μ _{M3}	q _{M3}	D _M

Then, the membership can be calculated by Equation (5).

$$\mu_{ij} = \left(\sum_{k=1}^c (l_{ij}/l_{ki})^{2/(m-1)} \right)^{-1}, \quad j = 1, 2, 3, \dots, c \quad (5)$$

where k is the number of iterations. The final effect of clustering is that the intraclass similarity is the smallest, and the similarity between classes is the largest. At this time, the sum of the weighted distances between the point and the center is the smallest. Therefore, when we get the minimum value that can be obtained by the objective function, we can further obtain the value of the clustering center of each classification and the membership value of each user relative to each classification, so as to obtain the final fuzzy clustering discrimination result. Finally, we calculate the final decision set based on the fuzzy multi-attribute decision-making (FMADM) algorithm.

C. MOBILITY PREDICTION ALGORITHM

When calculating the distance from user i to the adjacent BS, which is one of the characteristic parameter of the user’s position, we comprehensively consider the speed and acceleration of the user’s motion in the high-speed rail carriage, and construct a mobility prediction model. We set v_e as the maximum speed of user i , and a the acceleration which is obtained by the following equation:

$$a = a_{max} - (a_{max} - a_{min})(1 - v(t)/v_e) \quad (6)$$

where a_{max} and a_{min} are the maximum and minimum acceleration of user i respectively. Assuming that $v(t)$ is the instantaneous speed at the moment t , and order $\beta = (a_{max} - a_{min})/v_e$, then we can get the predicted acceleration $a(t)$ at the moment t by Equation (7), and obtain the velocity $v'(t)$ by Equation (8).

$$a(t) = \left[a_{max} - \frac{(a_{max} - a_{min}) \cdot v_0}{v_e} \right] \cdot e^{-\beta t} \quad (7)$$

$$v'(t) = a_{min} + \beta \cdot v(t) \quad (8)$$

where, v_0 is the initial velocity. Solve the differential Equations (7) and (8) to obtain $v(t)$, as shown in Equation (9):

$$v(t) = \left(\frac{a_{max}}{\beta} \right) + \zeta \cdot e^{-\beta t} \quad (9)$$

In the equation, $\zeta = \frac{v_0 + a_{min} + (v_e - v_0) \cdot a_{max}}{a_{max} - a_{min}}$ is a constant, which can be calculated by solving the differential equation. Assuming that $\beta_0 = a_{max} - \frac{(a_{max} - a_{min}) \cdot v_0}{v_e} \cdot e^{-\beta t}$, then

we can obtain the simpler calculating the equation of $v(t)$, as shown in (10):

$$v(t) = v_0 + \beta_0 \cdot t \quad (10)$$

As can be seen from the above equation, as long as the initial speed of the train and the current time t are known, then the speed value of the next moment can be calculated. We set the position of the user i at the current time as (x_0, y_0) , and the position of the next adjacent base station as (X, Y) . Given that the current speed of the train is $v(t)$, then, after T seconds, the position of the user i can be calculated by Equation (11), and the $d_i^{BS_{next}}$ can be obtained by Equation (12). Here, in order to ensure the accuracy of the prediction algorithm, we define T as the update period of the user’s measured position and the predicted position information. That is, every T seconds, we will update the current measured position information of the user and predict the position information at the beginning of the next T seconds.

$$\begin{cases} x = x_0 + v(t) \cdot T \\ y = y_0 + v(t) \cdot T \end{cases} \quad (11)$$

$$d_i^{BS_{next}} = \sqrt{(x - X)^2 + (y - Y)^2} \quad (12)$$

Next, we compare the obtained distance $d_i^{BS_{next}}$ with the radius r_{next} of the next adjacent cell. If $d_i^{BS_{next}} < r_{next}$, it indicates that the current location of user i is in the overlapping coverage area at the edge of the two cells, and will enter the adjacent next base station coverage area at a faster speed. Then we will adopt FCM algorithm to calculate the membership of each attribute and judge its category. If $d_i^{BS_{next}} \geq r_{next}$, it indicates that user i is far apart the next adjacent cell and will stay in the current cell for a period of time, then the user i will be determined as a central user directly and the membership function value will be set as 0, so as to reduce the resource waste and calculation caused by path loss.

D. DECISION-MAKING OF MOBILE USER CLASSIFICATION

Through the above two sections, we obtained the membership function value of the position attribute of user i and its mobility prediction result respectively. Next, we set reasonable weights for different attributes and used the weighted sum multi-attribute decision algorithm (MADM) to calculate the final type decision parameter value Q_i of user i . Refer to Table 1, we can carry out fuzzy processing on the attributes

through the fuzzy decision process. Where w_i denotes the weight of the i -th attribute, which has to satisfy the following formula of $\sum w_i = 1$; μ_{ij} represents the maximum membership of user i under attribute j . q_{ij} represents the set category corresponding to the maximum membership obtained by user i within attribute j , and $q_{ij} \in [0, 1]$. If $q_{ij} = 1$, it indicates that when we only consider the single attribute of j , the user i is an edge user of the current cell. Else if $q_{ij} = 0$, it means that the user i is a central user of the cell when we consider the only attribute of j . With the purpose of achieving a more scientific division of user i , we assign the corresponding weight w_i to each attribute, and then the weighted sum of the user attributes is calculated to obtain the classification discrimination parameter Q_i of user i according to the following Equation (13):

$$Q_i = \sum_{j=1}^c w_j \mu_{ij} q_{ij} \quad (13)$$

Finally, we determine the type of the user by comparing the size between the value of Q_i and 0.5, as shown in Equation (14):

$$D_i = \begin{cases} 0, & Q_i < 0.5 \\ 1, & Q_i \geq 0.5 \end{cases} \quad (14)$$

In this equation, we define D_i to represent the final type of the user i , where $D_i \in \{0, 1\}$. We also define U_c to represent the central user set, and U_e to represent the edge user set. If $D_i = 0$, then the user i will be judged as a central user. Else if $D_i = 1$, the user i will be judged as an edge user.

Algorithm 1 Mobility Prediction Based User Classification

- 1: Setting the parameters, including the position of BSes, user position, moving speed v and its acceleration a , etc.
- 2: Finding out three attributes of all mobile users: $d_i^{BS_c}$, $d_i^{BS_{next}}$, $SINR$.
- 3: Calculating the membership grades of these users using only two attributes $d_i^{BS_c}$ and $SINR$, and getting these membership grades of μ_{i1} and μ_{i3} and their types of q_{i1} and q_{i3} .
- 4: Estimating the train user position using the train speed and the acceleration, then obtain the attribute of $d_i^{BS_{next}}$.
- 5: If $d_i^{BS_{next}} < r_{next}$, calculating the membership grades of these users using only $d_i^{BS_{next}}$, and getting the membership grades μ_{i2} and its type q_{i2} ; Otherwise, the train user is seen as a center user with its membership grade $\mu_{i2} = 1$.
- 6: Making all train users' decisions using the sum of weights by Equations (12) and (13).

Now, the implementation steps of the mobility prediction based user classification algorithm are shown in Algorithm 1.

E. A MOBILITY PREDICTION BASED INTERFERENCE ALIGNMENT ALGORITHM

In this section, an IA algorithm based on the mobile user classification proposed above will be used to realize the interference management in the HSR wireless communication networks. First of all, we assume that the current base station provides communication and interference management services for the central users of the cell. Due to the edge users will move and switch to the next adjacent cell, we set up the next adjacent base station to provide communication service and interference management. Assuming that there are M transmitters corresponding to M receivers in the MIMO limited feedback channel, the number of transmitting antennas of the BS is N_t , the number of receiving antennas of the user is N_r , and the transmitting power of the BS is p_t , then the signal power received by user i can be calculated by Equation (15).

$$P_i = \sqrt{\eta_{m,i} p_i}, \quad i = 1, 2, \dots, M \quad (15)$$

where $\eta_{m,i}$ is the transmission path loss of the channel between transmitter m and user i , and p_i is the transmit power allocated to the user i . If $i \in U_c$, the transmit power will be assigned by the current service BS. If $i \in U_e$, then the next adjacent BS will distribute the transmit power for the service.

$$\begin{cases} i \in Cell_{present}, & i \in U_c \\ i \in Cell_{next}, & i \in U_e \end{cases} \quad i = 1, 2, \dots, M \quad (16)$$

As an effective interference management scheme, IA algorithm divides the signal space into the desired signal subspace and the interference signal subspace from the perspective of maximum the freedom degree. Since the dimension of the desired signal subspace determines the freedom degree and the throughput of the system, IA can increase the dimension of the desired signal subspace by compressing the dimension of the interfering signal subspace, so that the system capacity is not constrained by the network size and the system performance can be improved. The construction of transmitter precoding matrix and receiver interference suppression matrix is the key to achieve the IA.

In order to simplify the model, we only consider the downlink channel from the BS to the user because of the interoperability of the wireless channel. We define x_i is the transmitting data of the transmitter i , the matrix H_{ij} is a channel matrix from the transmitter j to the receiver i , the dimension of H_{ij} is $N_t * N_r$. Define the matrix V_j as a precoding matrix of the transmitter j . When the user i communicates with the BS i , the interference signal reaching the receiver is all the transmitted signals except the one from transmitter i . Therefore, in the IA technique, the channel matrix H_{ij} corresponding to the interference signal of the receiver i is multiplied by the linear set composed of the precoding matrix V_j , so that all the signal subspaces of the set are compressed to a single dimension, and the number of interference signals to be distinguished is effectively reduced. In this way, the receiver i can construct a receive suppression matrix U_i to achieve

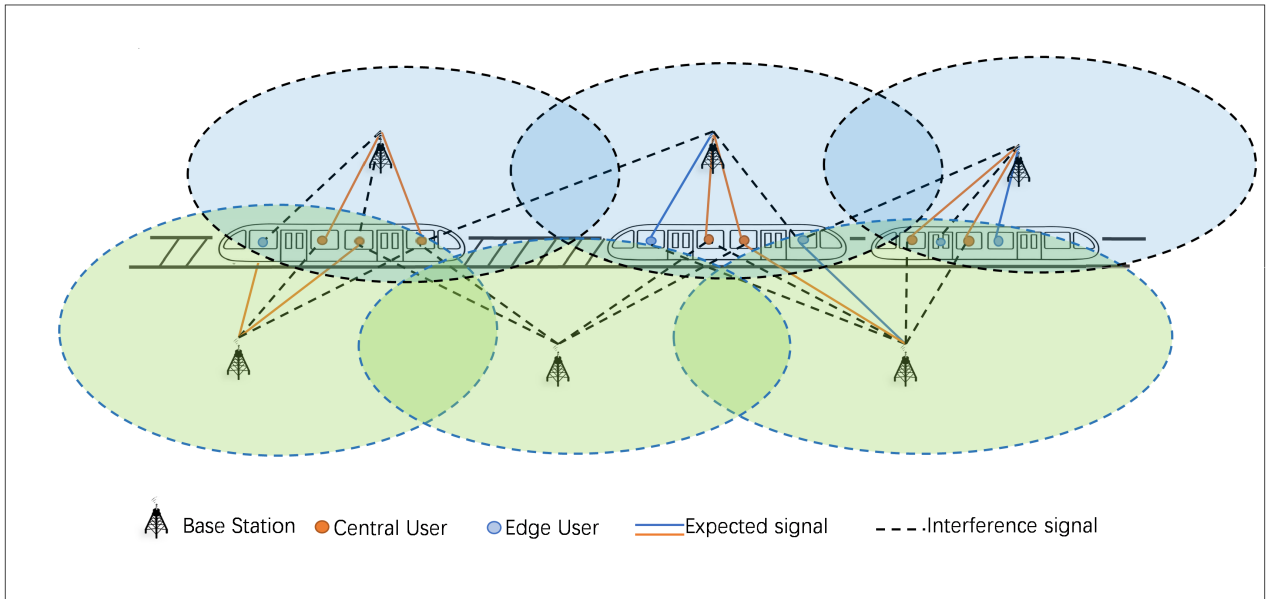


FIGURE 2. Schematic diagram of simulation scene.

interference forcing zero without affecting the reception of the expected signal.

We apply the above power allocation method based on the user classification to the classical Max-SINR IA algorithm [28] to realize the improved interference management strategy. Then the signal \hat{y}_i that finally received by the user i can be represented by the Equation (17):

$$\hat{y}_i = U_i^H P_i H_{ii} V_i x_i + U_i^H \sum_{j=1, j \neq i}^M P_j H_{ij} V_j x_j + U_i^H n_i \quad (17)$$

in this equation, n_i is an additive complex white Gaussian noise (ACWGN) with the average value of 0 and the variance of σ^2 . Then we can calculate the received SINR of user i by Equation (18).

$$SINR_i = \frac{U_i^H H_{ii} V_i (U_i^H H_{ii} V_i)^H \eta_{i,i} p_i}{\sigma^2} \quad (18)$$

Finally, according to the Shannon theory, we can obtain the total throughput of the network, as shown in Equation (19):

$$R_{\Sigma} = \sum_{i \in U_c} \log\left(1 + \frac{U_i^H H_{ii} V_i (U_i^H H_{ii} V_i)^H \eta_{i,i} p_i}{\sigma^2}\right) + \sum_{i \in U_e} \log\left(1 + \frac{U_i^H H_{ii} V_i (U_i^H H_{ii} V_i)^H \eta_{i,i} p_i}{\sigma^2}\right) \quad (19)$$

It can be seen from Equations (18) and (19) that system throughput in a high-speed moving environment is affected by the quality and power of received signals of each user. Reasonable user classification will significantly improve the effectiveness of IA, which is particularly important to ensure

the performance of the communication system. In particular, for the edge users, if the current base station still provides the services for them without considering the classification results, the received signal quality will continue to decline as the users rapidly get away from the current BS, and the BS needs to improve the transmission power to ensure the service quality, which will lead to the degradation of system performance. After considering the user classification, since the edge user is about to be handover to the next adjacent BS, we set the adjacent BS to provide service for the edge user. This not only reduces the load of the current BS, but also does not instantly bring a large number of users into a certain cell, so as to improve the total capacity of the system to a certain extent.

IV. SIMULATION AND DISCUSSION

A. ENVIRONMENT SETTING

In this section, we numerically evaluate our IA algorithm through a simulation topology as shown in Figure 2. In the simulation network environment, based on the single-hop HSR communication network architecture, we deployed a railway line with a length of 3km. On both sides of the track, six LTE BSes were deployed at 800m intervals, with the coverage radius of the cell being 800m. The length of each train is 100m and the number of users is 10. The positions of users were evenly distributed in the cars. In the above simulation scenario, the characteristics of high-speed train movement will bring significant doppler frequency shift effect. However, the improvement of train speed will not change the multipath model, only increase the doppler frequency shift of each path. Therefore, during the experiment, in order to ensure the rationality of the channel matrix, we set the

TABLE 2. Simulation parameters.

Parameter	Value
Cell radius r	0.8km
Train speed v	100 – 300km/h
Path loss L	$L = 20\log_{10}(d_i^{BS_c}/1000) + 20\log_{10}f + 32.4$
Transmit antenna N_t	4
Receive antenna N_r	8
BS transmit power	46dBm
Carrier frequency	$9.6 * 10^2$ MHz

doppler frequency shift on each path according to the train running speed, and considered the influence of train mobility on the channel by establishing the small-scale fading model of high-speed railway wireless channel. In the initial stage of the experiment, the train travelled at a random speed and a random acceleration from the beginning of the track, and the user randomly entered one of the nearest BSes on both sides of the track. The user type used the default value. Once the train run, the users were classified according to the algorithm in this paper. The interval between each experiment was 2s, the attribute weights were $w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$ respectively, and the other key parameters were summarized in Table 2. Based on the above setting, the network performances were achieved and summarized.

B. NETWORK PERFORMANCE ANALYSIS

To be specific, the performance indicators in our study include average bit error rate (BER), throughput and SINR of the users. We respectively verified the change of each performance indicators when the downlink SNR changes between -5dB ~ 20dB, and the train run at the five average speeds of 100km/h, 150km/h, 200km/h, 250km/h and 300km/h. The simulation results are shown in Figure 3, 4 and 5, each of the value is represented by its mean value obtained from the system carrying out 60 times of the algorithm per experiment.

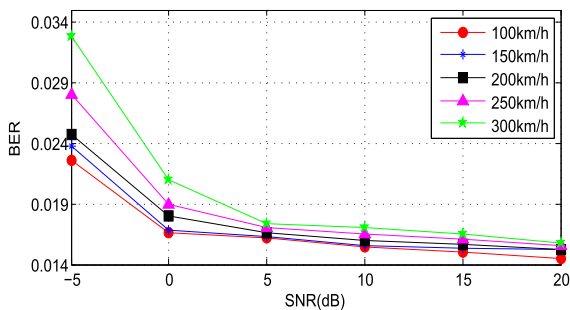


FIGURE 3. Sytem BER at different speeds.

From Figure 3, 4 and 5, we can see that the performance level of the wireless network in railway environment is greatly affected by train speed. With the increase of the train speed, the network throughput and the SINR of the signal received by the user both decrease, while the average BER increases. Specifically, Figure 3 reflects the relationship between the system BER and the train speed. In the

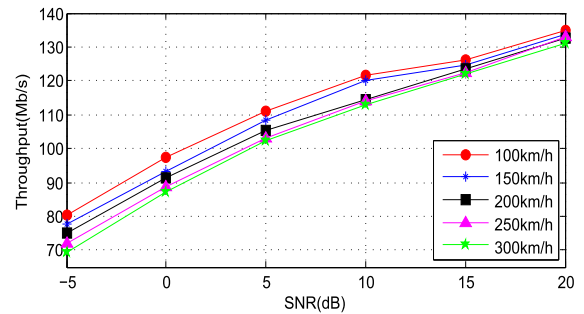


FIGURE 4. Throughput at different speeds.

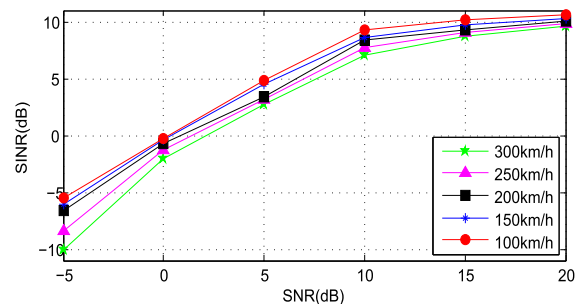


FIGURE 5. User received SINR at different speeds.

case of high-speed movement, the user has a large radial velocity relative to the BS, which makes the signal received by the user have a large Doppler Frequency Shift, resulting in the deterioration of the system BER performance with the increase of the speed. In addition, when the channel transmission quality is poor, that is, $SNR < 0dB$, the BER performance will significantly deteriorate with the increase of train running speed, when $SNR > 5dB$, the BER performance tends to be stable. As can be seen from Figure 4, when the train runs at different speeds, the value of attribute $d_i^{BS_{next}}$ will change, so the user classification results based on the mobility prediction will change accordingly. Therefore, when the train speed is high, at the next user classification moment, the user is likely to be out of the coverage range of the current BS, so it will be judged as an edge user, resulting in the decline of the current BS throughput. Figure 5 shows that the received SINR is greatly affected by the channel quality, especially when the channel transmission quality is poor. By comparing SINR curves at five average speeds, it can be seen that under the mobility prediction based IA algorithm presented in this article, the changing trend of received SINR performance is consistent at different speeds, and when the channel transmission conditions are good, the performance will be stable at about 10dB.

C. PERFORMANCE COMPARISON ANALYSIS

In order to further verify the performance of the algorithm, we applied the user classification algorithm based on mobility prediction(Classification-New), the user classification algorithm based on the SINR(Classification-SINR), the user

classification algorithm based on the Distance(Classification-Distance), the user classification algorithm based on the improved Distance-and-SINR(Improved D&SINR), as well as the User-free classification algorithm (non-Classification) to the IA algorithm model constructed in this article. In the HSR wireless communication network architecture established in section 4.1, we compared the network's performance including average BER, total system throughput and SINR of the users when the train average speed is 50km/h, 100km/h, 20km/h and 300km/h, respectively. Meanwhile, the SINR threshold of the Classification-SINR is 5dB, the Distance threshold of the Classification-Distance is $2/3r$, the Distance threshold L of Improved D&SINR is $0.4r$, and the area window size M is $0.2r$. The simulation results are shown in Figure 6, 7 and 8.

It can be seen from the Figure 6 that the system BER obtained by using the IA algorithm proposed in this paper is lower than that obtained by other algorithms. The main reason is that, when classifying the users, we not only consider the relationship between the users and the current service BS, but also adopt the mobility prediction method to get the location relationship between the users and the adjacent BSes. The more comprehensive the factors, the more reasonable the results. In addition, when classifying the mobile users on the train, the algorithm in this paper adopts the FCM algorithm to realize the single-attribute user division. This classification method is more reasonable and scientific than the hard partition method based on a fixed threshold.

As shown in Figure 7, in terms of total system throughput, Classification-New has the best performance and non-Classification has the worst performance. In the system without user classification, when the train completely enters a cell, the users on the train execute the strategy of switching the service BS at the same time. Users with different channel quality jointly accept the service of the same BS leads to better signal quality of users with good channel quality, while users with poor channel quality will also have poor signal quality, which is likely to cause polarization. For the BSes, when a train just enters a cell, the number of users in the cell will surge instantly, and a large number of users will share limited spectrum resources, which will lead to the decrease of system throughput and the uneven channel state will also lead to the increase of system BER. In the system with user classification algorithm, the edge users will be switched to the next BS to be entered, which not only reduces the load of the current BS, but also avoids bringing a mass of mobile users into a certain cell instantly. Therefore, the total capacity of the network can be increased to a certain extent.

In particular, as shown in Figure 7(a), when the train is running at a high average speed of 300km/h, the application of the IA algorithm based on Classification-New can greatly improve the total throughput of the system when the channel SNR is relatively low. When the $SNR < 15dB$, the total throughput of the system using Classification-New is optimal. This is because the algorithm takes into account the

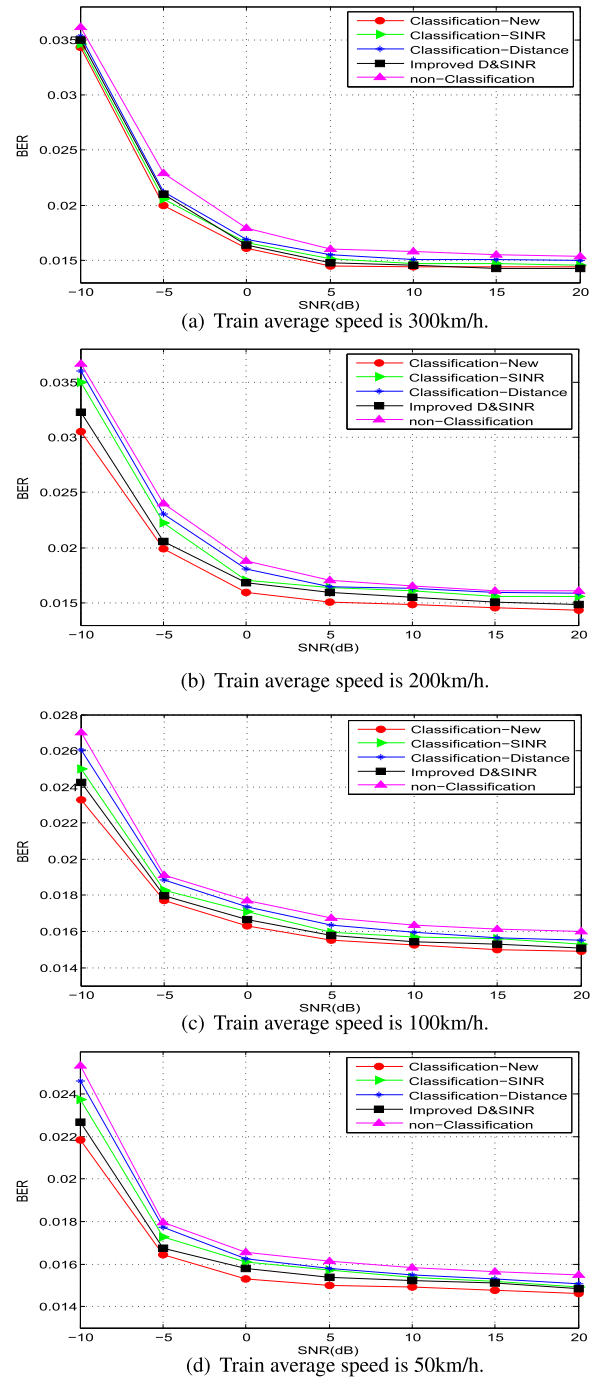
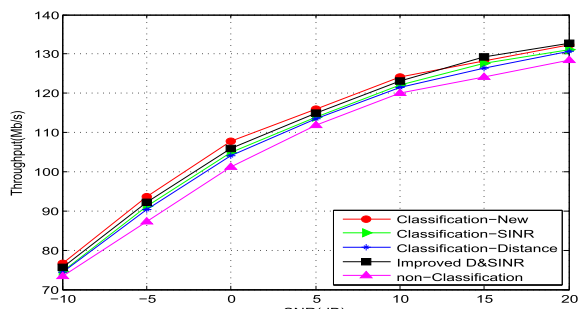
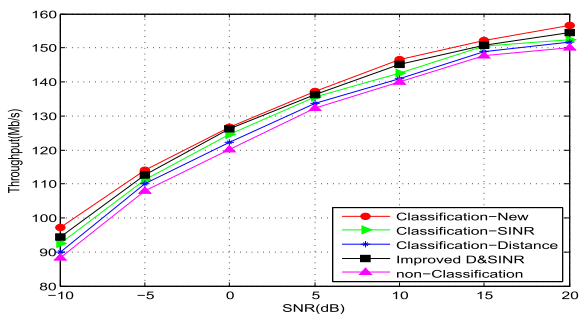


FIGURE 6. BER of different algorithms at different speeds.

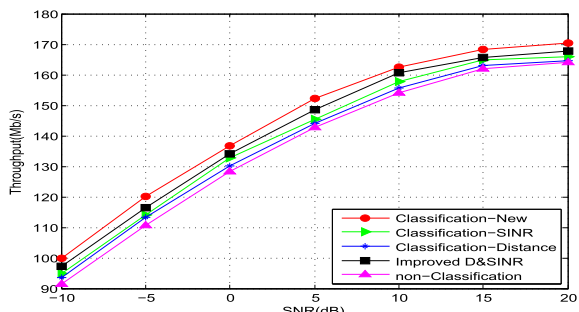
mobility of users, and fully considers the location relationship between the users and the current service BS as well as the location relationship between the users and the adjacent BSes, so as to make a reasonable classification and switching decisions, thus, the total throughput of the system is improved. When the $SNR \geq 15dB$, due to the good channel state, the channel quality of users is mainly affected by the distance between them and the service BS, while the Improved D&SINR algorithm divides users into three parts according to



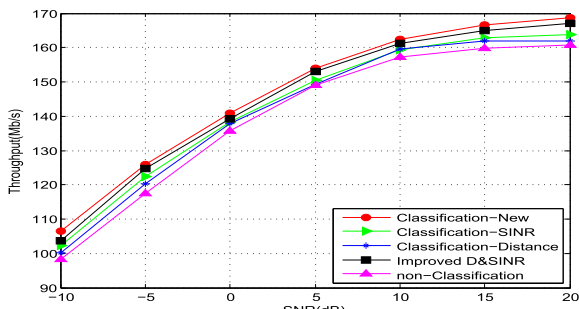
(a) Train average speed is 300km/h.



(b) Train average speed is 200km/h.



(c) Train average speed is 100km/h.

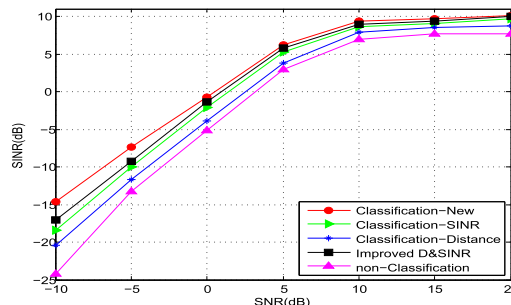


(d) Train average speed is 50km/h.

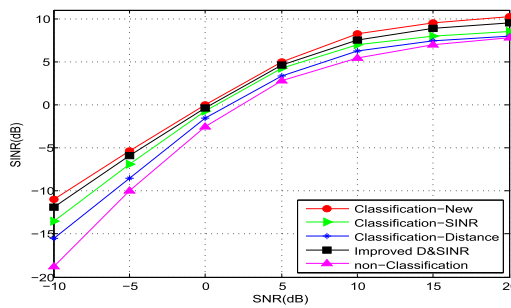
FIGURE 7. Throughput of different algorithms at different speeds.

distance, which is more accurate than other algorithms, so the system throughput is better.

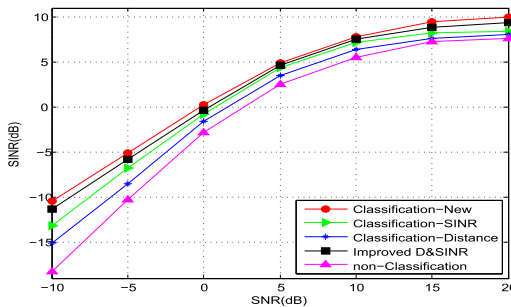
In terms of the performance index of *SINR* received by users, as shown in Figure 8, the IA algorithm based on Classification-New performs best. To be specific, in the case of poor channel transmission quality and high train average speed, it has more significant advantages. This is because the Classification-New algorithm is designed to improve the *SINR* of edge users, thereby closing the gap between the *SINR*



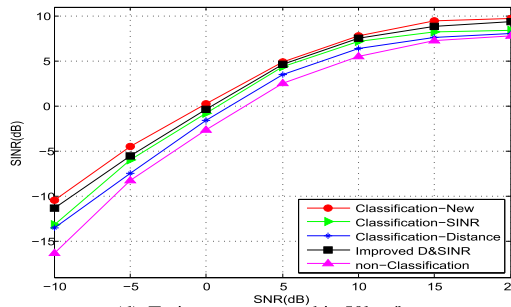
(a) Train average speed is 300km/h.



(b) Train average speed is 200km/h.



(c) Train average speed is 100km/h.



(d) Train average speed is 50km/h.

FIGURE 8. *SINR* of different algorithms at different speeds.

of center users and edge users, and therefore performs well in *SINR*.

V. CONCLUSION

In this work, in order to improve the service quality of mobile communication users in high-speed railway environment and ensure that users can minimize the signal interference between each other in the process of high-speed train operation, we classify the communicating users according to their mobile characteristics and improve the efficiency of

interference management. For obtaining a practical solution, combined with the distance from the user to current BS ($d_i^{BS_c}$), the distance from the user to the next BS ($d_i^{BS_{next}}$) and the current $SINR$, our FCM algorithm calculates the type of user under single attribute for $d_i^{BS_c}$ and $SINR$. By setting a reasonable weight and summing the above three attributes, the user's type is obtained. We then improve the power allocation method for users in the edge of the cell, and achieve effective interference management based on Max- $SINR$ IA algorithm. Our experimental evaluation prove that our algorithm is an effective method to improve user service quality and network performance in high-speed railway communication environment. In future work, we will consider using machine learning methods to optimize the attribute weights in the user classification algorithm.

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JIE SHENG received the Ph.D. degree in electronics and information technology from North China Electric Power University, China, in 2013. She is currently an Assistant Professor with the School of Rail Transportation, Soochow University, China. Her research interests include wireless communications, heterogeneous wireless networks, cognitive wireless networks, and applications of communication technology in intelligent transportation systems.



ZIWEN TANG received the B.S. degree in communication engineering from the School of Rail Transportation, Soochow University, in 2017. He was also involved in several projects in which these techniques are being applied in the fields of wireless communications. His research interests include dynamic multiagent systems and cognitive radio.



QIAOMING ZHU was born in Suzhou, Jiangsu, China, in 1963. He received the Ph.D. degree from the School of Computer Science and Technology, Soochow University, Suzhou, China, in 2006. He is currently a Full Professor with the School of Computer Science and Technology. His research interests include natural language processing, sentiment analysis, and discourse analysis.



YIMING WANG (Senior Member, IEEE) received the Ph.D. degree from the Nanjing University of Posts and Communications, China. She is currently a Full Professor with the School of Rail Transportation, Soochow University, China. She has authored or coauthored over 60 publications in the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, the IEEE TRANSACTIONS ON VEHICLE TECHNOLOGY, *Wireless Personal Communications*, and IEEE GlobalSIP Conference.

She was also involved in several projects in which these techniques are being applied in the fields of communication, robotics, and computer vision. Her research interests include wireless communications, cognitive wireless sensor networks, and intelligent transportation technology. She is also an Active Reviewer of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, and *Circuits, Systems, and Signal Processing*.



CHENG WU (Member, IEEE) received the M.Sc. degree in computer engineering from Concordia University, Canada, in 2005, and the Ph.D. degree from Northeastern University, USA, in 2010. He is currently an Associate Professor with the School of Rail Transportation, Soochow University, China. He has authored or coauthored over 50 publications in the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, the IEEE TRANSACTIONS ON VEHICLE TECHNOLOGY, the *Journal of Intelligent and Fuzzy System*, the *International Conference on Autonomous Agents*, and *MultiAgent Systems*. He was also involved in several projects in which these techniques are being applied in the fields of communication, and computer vision. His research interests include neural and fuzzy systems, dynamic multiagent systems, and intelligent human-computer interaction.



BO AI (Senior Member, IEEE) received the M.S. and Ph.D. degrees from Xidian University, Xi'an, China, in 2002 and 2004, respectively. He was with Tsinghua University, Beijing, China, where he was an Excellent Postdoctoral Research Fellow, in 2007. He is currently a Professor and an Advisor of Ph.D. candidates with Beijing Jiaotong University, Beijing, where he is also the Deputy Director of the State Key Laboratory of Rail Traffic Control and Safety. He is also with the Engineering College, Armed Police Force, Xi'an. He has authored or coauthored six books and 140 scientific research articles, and holds 26 invention patents in his research areas. His research interests include the research and applications of orthogonal frequency-division multiplexing techniques, high-power amplifier linearization techniques, radio propagation and channel modeling, global systems for mobile communications for railway systems, and long-term evolution for railway systems.