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A NOVEL METHOD FOR REDUCING THE EFFECT OF DOPPLER FREQUENCY SHIFT IN HIGH-SPEED RAILWAY MOBILE COMMUNICATION USING MACHINE LEARNING

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Abstract. Currently, high-speed railway systems are rapidly expanding worldwide, necessitating reliable and efficient mobile communication solutions. However, the Doppler frequency shift caused by the high speeds of trains presents significant challenges to communication systems, particularly those using OFDM in LTE. This paper presents a novel for Doppler frequency compensation in high-speed railway communication based on the results of estimating the train's velocity using machine learning algorithms. By leveraging advanced algorithm such as neural networks, our method dynamically predicts and compensates for Doppler shifts in real-time. In this proposed novel, the Doppler frequency value is calculated based on the actual train's velocity and the scenario of a high-speed railway, then the Doppler frequency is used to compensate the carrier frequency offset (CFO) directly at the Access Point (AP) device on the train. We conduct simulations to evaluate the effectiveness of our proposed solution in a high-speed railway scenario. The results demonstrate a marked improvement in communication reliability and data integrity, highlighting the potential of machine learning to enhance the performance of mobile communication systems in high-speed railways. The results of the proposed model are evaluated based on the system's bit error rate BER after the CFO compensation decreases and the ratio of average energy per bit (Eb) to noise power density (N0) (Eb/N0) increases. This shows that the proposed solution works effectively and reduces the system's bit errors while improving the communication performance. This study opens new avenues for integrating intelligent systems in transportation networks, ensuring seamless connectivity, and improving passenger experience.

Keywords: Doppler compensation, High Speed Railway, Doppler, Carrier Frequency Offset, Machine Learning, Deep Learning.

1. INTRODUCTION

The birth and development of railway transport have become a revolution in the transport industry since the early years of the 19th century. After centuries of refinement and development, in recent years, many high-speed railway works have been built and installed: TGV POS high-speed train in France, ICE train in German, ETR 400 train in Italy, etc., Shinkansen in Japan, the High-speed Railway - HRS with a speed of 575 kph [1]. Currently, in Vietnam, the government is also researching and implementing a plan to build a North-South high-speed railway, Hanoi - Ho Chi Minh City. As these systems expand globally, ensuring reliable mobile communication for passengers and operational management is critical. However, one of the significant challenges in maintaining seamless communication in high-speed railways is the Doppler frequency shift, the phenomenon that occurs due to the relative motion between the train and the communication infrastructure. The rapid advancement of high-speed railway systems has necessitated reliable and robust mobile communication solutions. One of the significant challenges in this domain is the Doppler frequency shift, which adversely affects the performance of communication systems. The International Railway Union (UIC) has categorized railway communication services into two main categories: services related to train operation and passenger information services (voice, data, images, video) [2], [3]. During high-speed train movement, Doppler frequency shift occurs due to relative motion between the transmitter and receiver, increasing the bit error rate BER on the transmission channel and reducing the quality of communication. The problem of eliminating Doppler frequency shift for HSR plays a significant role in directly affecting the transmission signal, reducing signal delay, and ensuring the continuity of monitoring and control information from the operation centre to the equipment on the train.

The European Train Control System (ETCS), China Train Control System (CTCS), and Communication-Based Control System (CBTC) including train dispatching commands, train operation information, train safety warnings, as well as signal equipment dynamic monitoring information are all provided by the Global System for Mobile Communications for Railways (GSM-R) [3], [4], [5]. With the rapid development of mobile communication and the need for broadband communication, railway telecommunication services not only replace GSM-R solutions but also provide high-speed communication channels for passenger information services. The Doppler frequency shift results in the alteration of signal frequencies, leading to issues such as signal distortion, degradation of data integrity, and increased error rates in communication systems [1]. Traditional methods to mitigate these effects often involve complex hardware solutions or static signal processing techniques, which may not adapt well to the dynamic and high-speed nature of railway environments. The effect of Doppler frequency on subscriber moving at 30 kph is only about 8.3 Hz but calculating in the speed scenario of the high-speed train at 360-540 kph, this frequency shift value has increased to 833 Hz-1300 Hz, 100 times higher than the Doppler frequency value of subscriber moving at low speed.

Orthogonal Frequency Division Multiplexing (OFDM) is a key modulation scheme used in Long-Term Evolution (LTE) systems, known for its high spectral efficiency, robustness to multipath fading, and ease of implementation. OFDM divides the available spectrum into multiple orthogonal subcarriers, each modulated with a low data rate stream. This parallel transmission reduces the impact of frequency-selective fading and improves the system's ability to manage high data rates and wide bandwidths. The orthogonality of the subcarriers in OFDM ensures that they do not interfere with each other, making it an efficient way to maximize the use of available spectrum. However, the main disadvantage of OFDM spread spectrum technique is its sensitivity to small frequency differences at the transmitter and receiver, known as frequency shift [1]. This frequency shift can be caused by the Doppler shift due to the relative motion between the transmitter and the receiver, or by the difference between the frequencies of the local oscillators at the transmitter and the receiver. There are studies have proposed different solutions to reduce the influence of Doppler frequency in high-speed railways in LTE-R railway communications, as presented in [6], [7]. In [6], the Doppler frequency estimation and compensation in LTE-R is presented. This method estimates the CFO in the received signal and then transmits this CFO value to the eNodeB to compensate for the frequency shift. However, the accuracy of this method has not been confirmed. Study [7] presents a solution to estimate the Doppler frequency shift in a Massive MIMO multi-antenna system based on the direct Fourier transform (DFT) combined with a theoretical channel model. However, the methods mentioned are complex and demand significant time and resources to implement. In this study, we optimized the Doppler frequency shift calculation method based on the calculation of actual train speed and specialized scenarios of high-speed railways to propose a CFO compensation method for the HSR problem.

In recent years, machine learning has emerged as a powerful tool for solving complex, nonlinear problems across various fields. Artificial intelligence (AI) and Machine learning (ML) are of great concern in being applied in mobile communications to solve problems such as radio resource allocation, signal coding and decoding and channel estimation. Its ability to learn from data and make real-time predictions offers a promising avenue for addressing the challenges posed by Doppler frequency shifts in high-speed railway communications. By integrating machine learning algorithms into the communication framework, it is possible to dynamically predict and compensate for frequency shifts, thereby enhancing the reliability and performance of the communication system. Deep learning will be an outstanding tool in dealing with complex computational problems in performing channel estimation in highly mobile environments. In study [8], DL is applied to implement the modulation, coding, and payload length change mechanism for railway transmission lines adapting to the Vehicle-to-vehicle (V2V) channel conditions. Two different DL algorithms are proposed for finding the optimal transmission path for multi-hop connection of V2V communication [9] or applying DL in estimating the distance between vehicles for location determination [10]. This paper explores the application of machine learning techniques to mitigate the effects of Doppler frequency shifts in high-speed railway mobile communication. We propose a novel approach that leverages neural networks to model and correct the frequency shifts in real-time. Our methodology uses data sets from railway communication systems, training machine learning models to predict Doppler shifts accurately, and implementing these models within the communication protocol to adjust signals dynamically.

Through simulations and calculates BER value, we demonstrate the effectiveness of our approach in improving communication quality and reducing error rates. This model indicates that machine learning can significantly enhance the robustness of high-speed railway communication systems, ensuring consistent and reliable connectivity for passengers and operational systems alike.

The rest of this paper is organized as follows: Section 2 presents system model and algorithm model. Section 3 presents simulation setup and results of Doppler frequency shift compensation proposed model. Finally, Section 4 concludes the paper and outlines potential future research directions.

2. SYSTEM MODEL AND ALGORITHM MODEL

2.1. System model

Typical systems of current telecommunication networks often apply the fact that all mobile devices of users - Mobile Stations (MSs) are directly connected to 4G mobile Base Stations (eNodeBs). When the train is moving at high speed, all MSs will simultaneously connect back and forth between neighboring eNodeBs, at the same time the impact of Doppler phenomenon during the train's movement causes Doppler frequency shift, which greatly affects the train's operational control information, causing unsafety and reducing the quality of mobile service of users.

Therefore, we proposed a model applied in the HSR communication system as follows: the signal from the eNodeBs is received at an antenna outside the train of the Access Point device to minimize the number of mobile devices performing handover (HO) to the same eNodeB at the same time. The Access Point will receive signals from eNodeBs and determine and estimate the train's velocity using deep learning, then calculate the Doppler frequency shift caused by the difference in the train's velocity and compensate for the Doppler frequency directly, and finally, an antenna inside the train will transmit the signal after frequency compensation to real-time monitoring and control devices on the train and service users as shown in Figure 1. This model reduces the calculation time to compensate for frequency shifts and reduces the impact of Doppler frequency shifts caused by conventional communication methods.

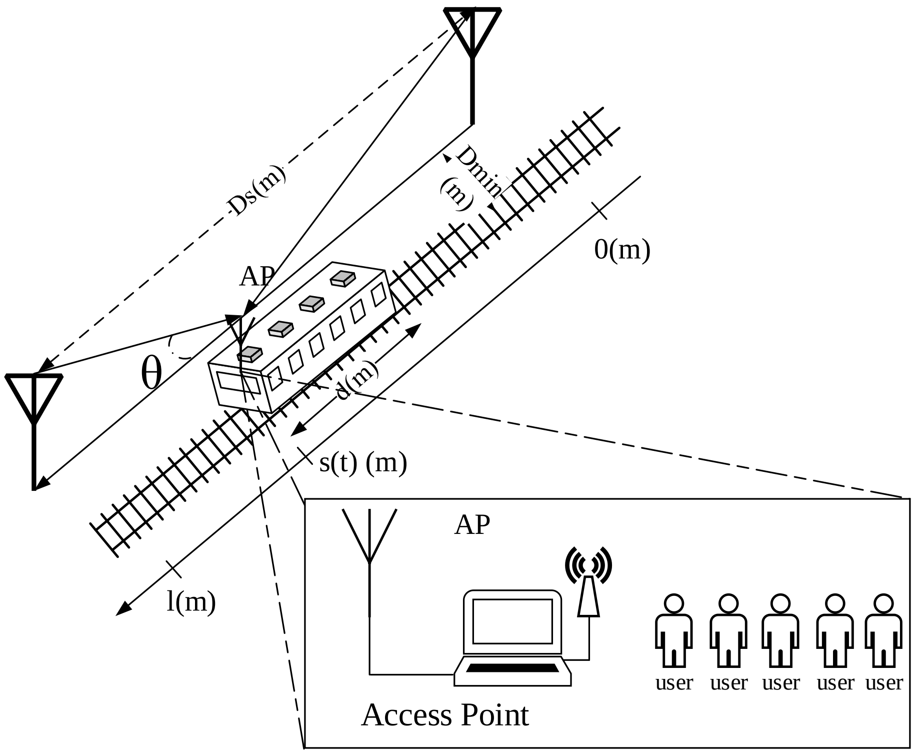

Figure 1. Doppler frequency shift compensation scenario proposed [11].

In this scenario, the eNodeBs are placed close to the railway $D_{min}(m)$~$2(m)$, the distance between two consecutive transmitting stations, the train's direction is predetermined. The standard train speed follows the Maximum Speed Order.

2.2. Mathematical model and channel model

The mathematical model in this proposal is based on the actual high-speed railway context and is presented as follows.

In the HSR system, the train always moves on a fixed railway and the train's direction of travel has been designed and predetermined. In addition, the train's speed is also specified for each section of the railway. However, not all the time the train moves at the predetermined speed, at some times, due to the influence of external factors, the train's speed may deviate from the conventional speed. Moving at a speed different from the conventional speed $\Delta v(mps)$ will lead to incorrect calculation of the Doppler frequency shift. Therefore, accurately determining the instantaneous speed of the train is an effective solution for calculating the Doppler frequency shift compensation.

In this paper, we used a deep learning neural network algorithm to determine the speed of train at instantaneous times, based on the algorithm model shown in Figure 2.

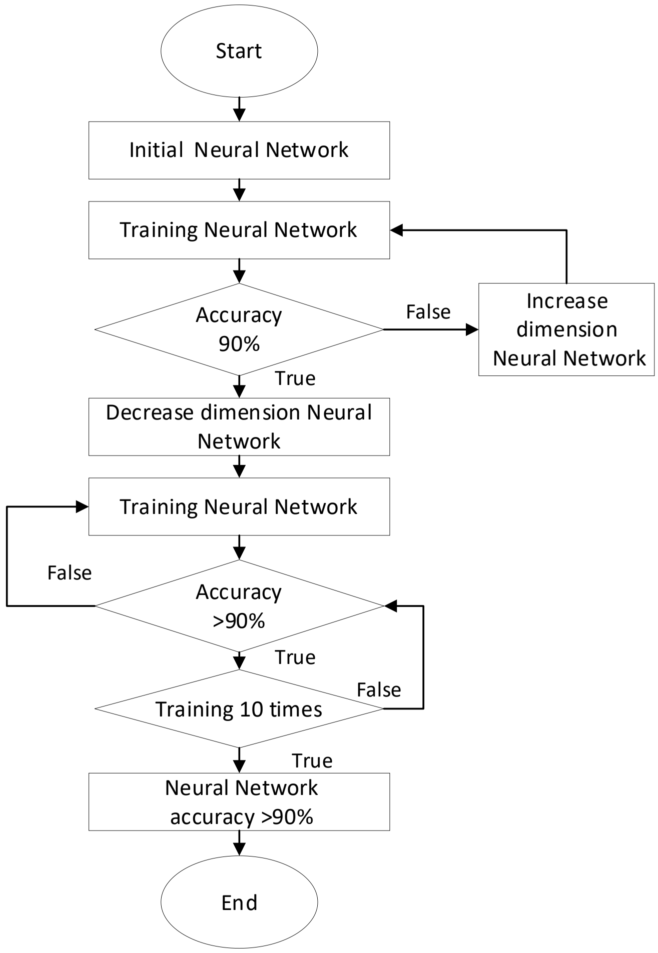

Figure 2. Neural network flow chart.

- Step 1: Initialize the Neural Network model.
- Step 2: Train the Neural Network model based on the test data set.
- Step 3: Check the accuracy of the results, if the accuracy is greater than 90%, reduce the size of the data set and continue training.
- Step 4: Check the accuracy of the model after reducing the size, if it is greater than 90%, then train the data 10 times, equivalent to 10 hidden layers of the Neural network.
- Step 5: Check and give the result.

In wireless communication, incorrect estimation of the Doppler frequency shift effect will lead to inaccurate frequency shift compensation, which reduces the efficiency of the Doppler compensation method, thereby reducing the transmission efficiency of the system. The problem assumes that the input data set of the train speed estimation block is an independent function in which the speed value is determined at each sampling time. In this study, we use the Neural Network algorithm to determine the instantaneous velocity of the train $v(t)(mps)$ combined with the conventional standard velocity $v_0(t)(mps)$, we can calculate the instantaneous Doppler frequency $f_d(t)(Hz)$ affecting the system and then perform frequency compensation as soon as the Doppler frequency shift value is determined.

When the train moves at high speed, the difference in frequency deviation is larger, the Doppler phenomena effect causes a change in frequency which affects the signal quality of the system [11].

The Doppler frequency is calculated by Equation (1) according to the system model proposed in Figure 1

$$f_d(t) = f_c \frac{v(t)}{c} \cos\theta(t) \tag{1}$$

Where:

- $f_d(Hz)$: Doppler frequency shift
- $f_c(Hz)$: the central carrier frequency of operation eNodeB
- $v(t)$: train speed (kph), (mps)
- $c(mps)$: constant value - the speed of the electromagnetic wave $3.10^8(mps)$
- $\theta(\deg)$: the angle formed by the signal and the train direction.

From Equation (1), we see that the Doppler frequency $f_d(t)$ depends on the value $\cos\theta(t)$,velocity $v(t)(mps)$ and acceleration $a(mps^2)$.

The $\cos\theta(t)$ value is determined based on the relative motion position of the train at that time (t) with $s(t)$ the location of the nearest eNodeB, Figure 3. The direction of moving train is also used to determine the value $\cos\theta(t)$ shown in Equation (2) (3) and (4):

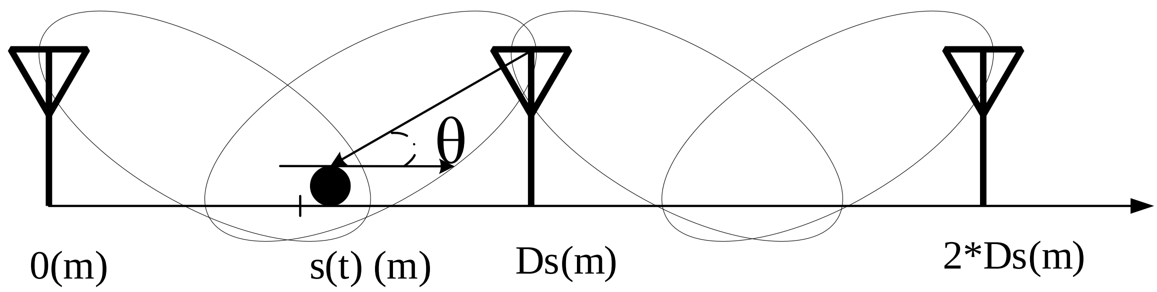

Figure 3. High-speed railway communication model (Source: Authors).

$$\cos\theta(t) = \frac{\frac{D_s}{2} - s(t)}{\sqrt{D_{\min}^2 + \left[\frac{D_s}{2} - s(t)\right]^2 + h^2}}, 0 \le s(t) < \frac{D_s}{2} \tag{2}$$

$$\cos\theta(t) = \frac{D_s - s(t)}{\sqrt{D_{\min}^2 + \left[D_s - s(t)\right]^2 + h^2}}, 0 > s(t) \ge \frac{D_s}{2} \tag{3}$$

$$\cos\theta(t) = \cos\theta\left(t \bmod \frac{D_s}{v}\right), s(t) > D_s \tag{4}$$

In this novel, Doppler frequency is the main research object, so we used the assumption that the system has synchronization in time as well as oscillation frequency.

In practice, the railway traverses various types of terrain areas such as urban areas, suburbs, rural areas, mountainous areas, tunnels, intersections with bridges and roads, etc. In the HSR, it is assumed that eNodeB stations are placed consecutively, evenly spaced at a given distance, and parallel to the train direction. We do not consider the case of slow fading due to the influence of obstacles on the transmission line from eNodeB to AP, the signal propagation between the eNodeB and the antenna at the AP access point without interruption by obstacles and is always in line of sight (LOS) to reduce interference effects of multipath on the system.

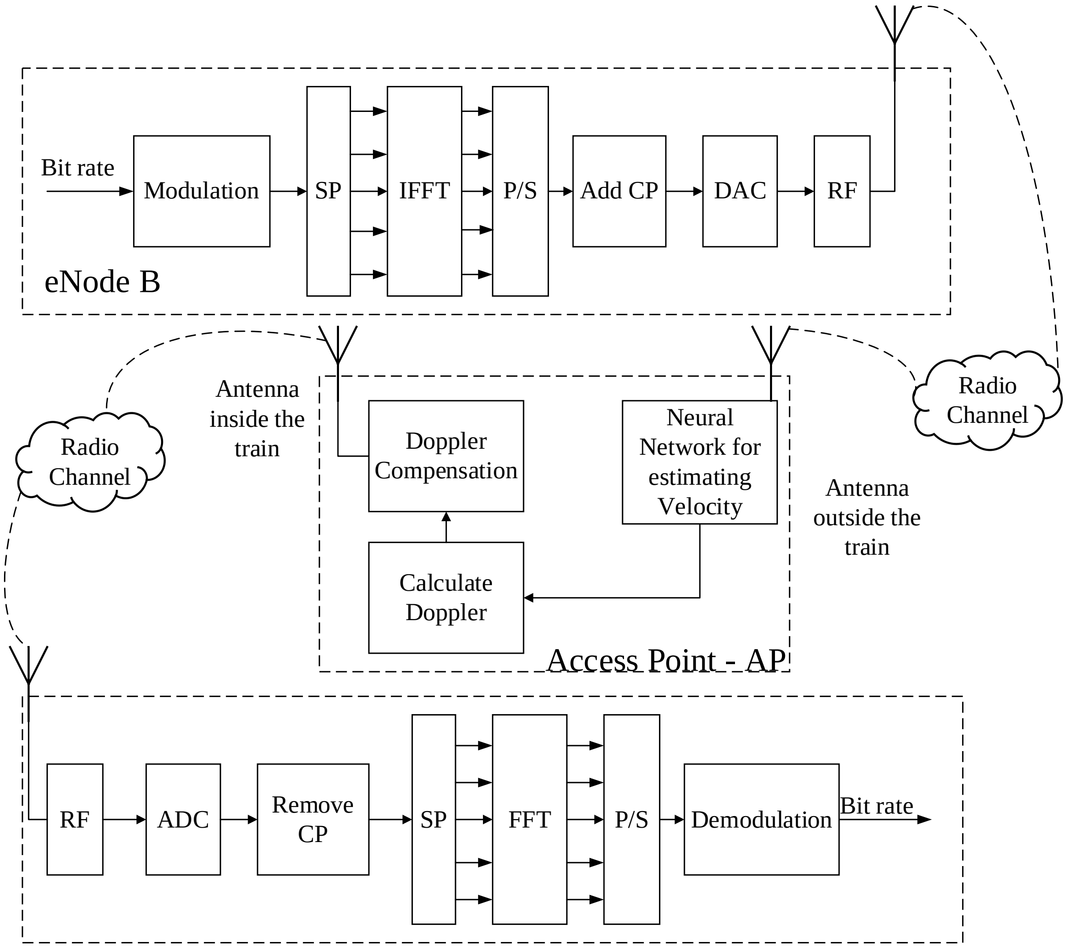

Figure 4. Details of the proposed HSR system model [11]

The proposed system model in Figure 4 shows the addition of the actual train speed estimation block and CFO compensation block at the on-board AP device. The actual train speed estimation block based on the Neural network model with input data being the train speed data set determined based on the speedometer while the train was moving has been presented above.

In the transmitter, data from the eNodeB is divided into bit streams, modulated at the baseband, and then passed through a serial-parallel conversion block. The output signal from the IFFT block is inserted with a cyclic prefix (CP) and passes through the DAC block to generate the OFDM signal [11-13].

The transmission channel between the onboard AP and the eNodeB is affected by time changes, sensitive to Doppler frequency. Therefore, the RICE channel is applied according to the D2A WINNER II scenario [14], [15]. The signal is then transmitted through the RICE multi-path channel with GAUSS interference conditions.

In this case, the TDL impulse response of the one-tap channel f_D is expressed by Equation (5)

$$H(t) = A(t).\exp(j2\pi f_D t) \tag{5}$$

Where:

$$A(t) = A_r.\sqrt{P}.\frac{1}{\sqrt{N}}\sum_{n=1}^{N}\{a_n\} \tag{6}$$

Where A_r is the magnitude of the received signal, P is the average power of "one tap", N is the number of scatters, $a_n \sim N(0,1)$ is a random complex variable Gaussian with values from 0 to 1.

Assume that the transmitted signal is an OFDM sample from the RU to the AP:

$$S(t) = \sqrt{s(t)}.\exp(j2\pi f_c t) \tag{7}$$

Then the signal was received at the antenna on top of the train is given by:

$$Y_i(t) = H_i(t).S(t) + N_i(t) \tag{8}$$

H_i and N_i is channel response and the noise received from the antenna, respectively.

$$Y_i(t) = A_i(t).\exp(j2\pi f_D t).\sqrt{s(t)}.\exp(j2\pi f_c t) + N_i(t) \tag{9}$$

$$\rightarrow Y_i(t) = A_i(t).\sqrt{s(t)}.\exp\left[j2\pi t\left(f_c + f_D\right)\right] + N_i(t) \tag{10}$$

Where f_D is the actual Doppler frequency shift value of the received signal at the AP on the train.

Because the Doppler frequency shift f_d is calculated based on the actual train speed and the direction of the train according to Equation (1).

At AP on board, when receiving signals from eNodeB, the Doppler frequency offset will be compensated to eliminate interference between carriers ICI noise. The AP calculates the Doppler frequency to compensate for the frequency to remove – ICI [12-14].

The signal after Doppler frequency compensation at the AP is:

$$Y_i(t) = A_i(t).\sqrt{s(t)}.\exp\left[j2\pi t\left(f_c + f_D\right)\right].\exp\left(j2\pi f_d t\right) + N_i(t) \tag{11}$$

$$\rightarrow Y_i(t) = A_i(t).\sqrt{s(t)}.\exp\left[j2\pi t\left(f_c + f_D - f_d\right)\right] + N_i(t) \tag{12}$$

If the AP performs satisfactory frequency compensation calculations $f_d = f_D$, the Doppler frequency shift in the system can be completely remove.

Since the simulation model is at baseband with Sub-channel Band width of $\Delta f = 15kHz$, the CFO can be calculated according to the following Equation (13):

$$\varepsilon = \frac{f_d}{\Delta f} = \frac{f_c v(t)}{c\Delta f} \tag{13}$$

3. SIMULATION SETUP AND RESULTS

Researching the characteristics of Doppler frequency shift in high-speed railways is one of the most important tasks of railway information systems because Doppler frequency shift is the main cause of subcarrier loss of orthogonality, causing ICI interference that greatly affects the quality of the communication system. In addition, the impact of the Doppler frequency shift also affects the accuracy and reliability of channel modeling in HSR radio communication and affects train control information.

In railways, the train's moving speed is specified for each section of the distance according to the Maximum Speed Order. There are 4 typical train travel cases: the train accelerates when leaving the station, the train moves straight with constant velocity, the train decelerates when arriving at the station and the train suddenly decelerates when encountering an incident. In this paper, we simulate Doppler frequency shift compensation in the case of a train moving straight on the rail.

There are many factors that affect the movement of the train, leading to the train's velocity not being able to maintain the value according to the Maximum Speed Order. Determining the correct speed of the train can determine the effect of the Doppler frequency shift, leading to the accurate calculation of the Doppler shift compensation.

Figure 4 shows the results after performing the estimation of the train's velocity prediction based on the Neural network algorithm presented in Part 1.

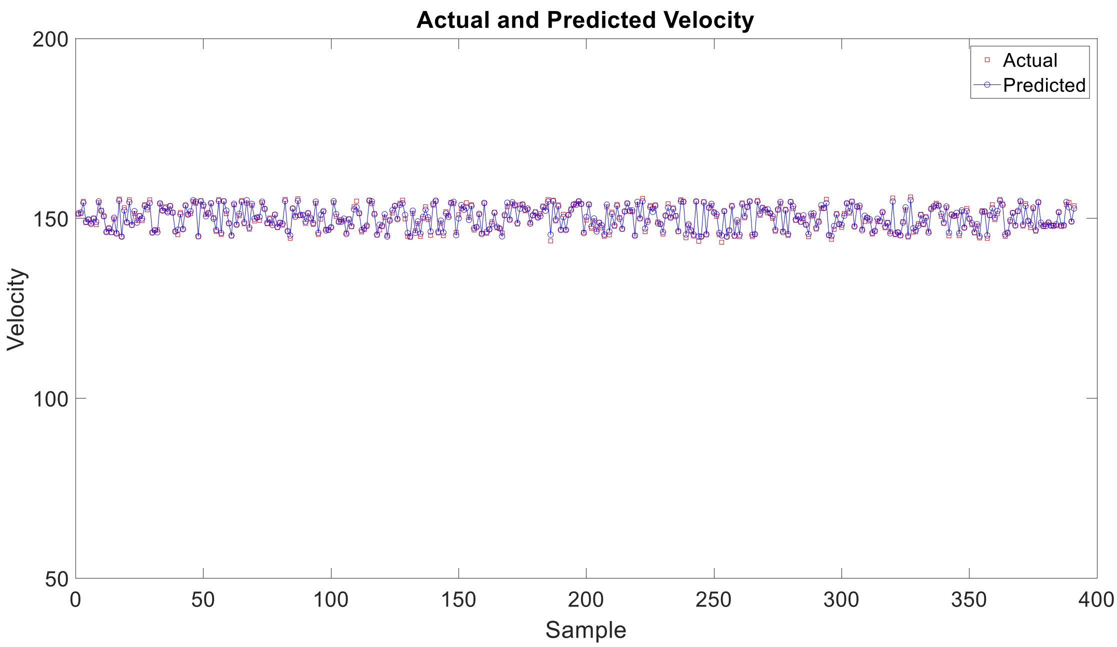

Figure 5. Actual and Predicted Velocity

The calculation results in Figure 5 show that the actual velocity and the velocity after estimation have differences, affecting the results of calculating the Doppler frequency shift.

Evaluating the Neural network algorithm through the Mean Squared Error (MSE) value is a statistical measure that evaluates the quality of a regression model by measuring the average magnitude of the error between the model's predicted values and the actual values. MSE is calculated by squaring the errors (predicted values minus actual values), and then calculating the average of those squared errors. The formula for MSE is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \overline{y_i}\right)^2 \quad (14)$$

Where:

- n : Number of samples
- y_i : Actual value
- $\overline{y_i}$: Predicted value

Mean Squared Error: 0.25 is quite low, which indicates that the model's predicted value is close to the actual value, meaning that the model has high accuracy. This means that the mean squared deviation between the predicted velocity value and the actual velocity value is quite small, indicating that the model performs relatively well.

Correctly determining the instantaneous velocity $v(t)(mps)$ increases the accuracy of the frequency offset estimation, which will be presented in the following section.

The neural network model used is a Feedforward Neural Network, employing a regression method to predict continuous values (in this case, the prediction object is the train's velocity). This model is an MLP (Multilayer Perceptron) Neural Network.

The structure of the neural network model used in this study consists of three layers: an Input layer, a Hidden layer, and an Output layer.

The proposed algorithm features only one hidden layer, making it easy to set up and not requiring significant computational resources. This is suitable for simple regression problems where the data has a linear or near-linear relationship. The reduced computation time for velocity estimation minimizes the time needed to calculate the Doppler frequency for the proposed system. Consequently, frequency compensation occurs almost immediately at the Access Point (AP) device on the train, preventing disruptions to the train's control signals and passenger service information.

On the other hand, using a minimal number of layers in a machine learning model can increase the Mean Squared Error (MSE) value. However, as analyzed, this model can achieve a low MSE for a model with simple, linear, or near-linear datasets, ensuring the accuracy of the prediction results. Additionally, using a neural network model with fewer layers can help avoid the problem of overfitting, ensuring that the model still performs well with new datasets.

The simulation scenario is based on the system model presented in section 1 along with the 4G - LTE radio parameters in Table 1. Sampling frequency $f_s = 15.36Hz$, QPSK modulation method, number of FFT and IFFT are 1024, the guard interval is $\frac{1}{4}T_{symbol}$.

Simulations are performed on the RICE channel with the channel coefficient $K=4$, $K=16$ representing the fading level on the channel.

Table 1. Simulation parameters in the system.

Parameters	**Value**
Cell diameter	$500m$
Number of OFDM subchannels	$N=1024$
The average velocity train according to the Maximum Speed Order	$v_0=150mps=540kph$
Channel Bandwidth	$B=20MHz$
Modulation	QPSK
Sampling frequency	$f_s=15.36Hz$
Sub-channel Band width	$\Delta f=15kHz$
Frequency of operation eNodeB	$f_c=2.6GHz$
Guard interval	$\frac{1}{4}T_{symbol}$
Antenna height of the transmitter	h=4m
Doppler frequency	$f_d=1300Hz$
Radio channel	Rician ($K=4$, $K=16$)

Figure 6 illustrates a continuous variation in the Doppler frequency, with the values oscillating around ±1300 Hz during the straight-line motion of the train. This continuous change in frequency is attributed to fluctuations in the train's instantaneous velocity as it travels between stations. As the train accelerates or decelerates throughout its journey, the velocity at any given moment influences the observed Doppler frequency. The frequency shift, which can be calculated using the formula provided in Equation (1), illustrated the dynamic relationship between the train's movement and the Doppler effect, shows how the speed changes directly impact the frequency shift. The Doppler frequency shift is determined by Equation (1).

The Doppler frequency changes to 0 Hz when the train moves across the service area boundary of 2 consecutive eNodeBs and performs handover between the two eNodeBs. After the train passes the coverage area boundary and performs handover with the eNodeB, the value of the Doppler frequency is also inverted by the sign of the cosine value in the expression determining the Doppler frequency value.

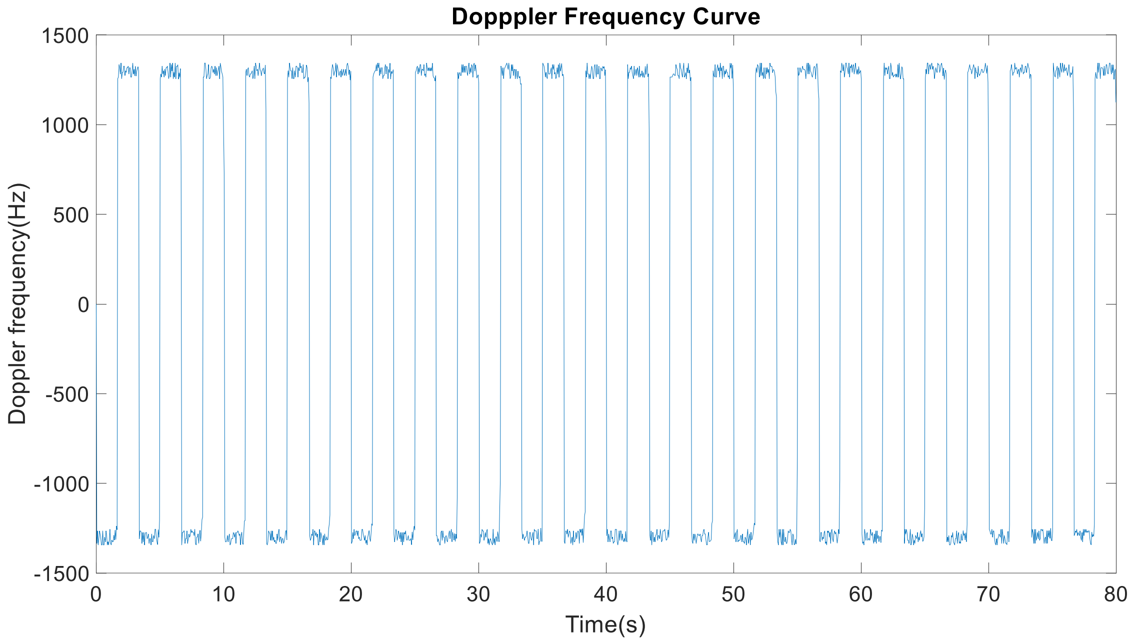

Figure 6. Effect of Doppler frequency when the train moves between eNodeBs in the RICE channel.

Figure 6 also illustrates that the Doppler frequency has an influence on the channel quality during the train's motion. From there, we solved the calculation and frequency shift compensation. Figure 7 shows bit error rate value represents the BER curve after CFO compensation has been reduced sharply, close to the BER theoretical. This proves that the algorithm is highly effective.

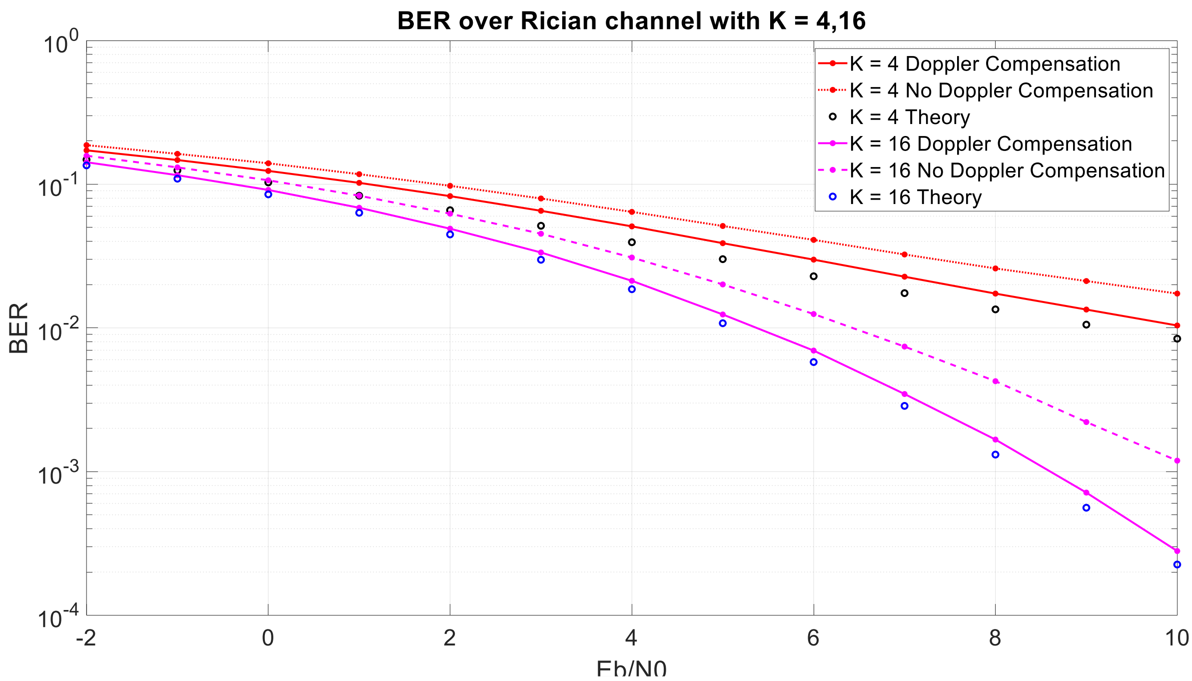

Figure 7. BER after using the CFO compensation algorithm, on the RICE channel with channel.

The simulation results of the BER in Figure 7 illustrates the correlation of the BER theoretical curve, the BER curve when affected by the Doppler frequency shift and the BER curve after CFO compensation on the RICE channel has fading coefficients $K = 4$ and $K = 16$.

Figure 7, we can see that the Bit error rate value shown by the actual BER curve without CFO compensation has a significant difference with the BER theoretical value, showing the influence of Doppler frequency shift to reduce sharply the service quality of the system.

After implementing the CFO compensation algorithm, the BER value after compensation decreases asymptotically to the BER theoretical value, showing that the BER of the system has decreased sharply, the transmission channel quality has been improved and the performance of the system has been improved.

4. CONCLUSION

This paper proposes a novel approach to mitigate the impact of Doppler frequency shifts using machine learning techniques. By leveraging advanced algorithms such as neural networks, our method dynamically predicts and compensates for Doppler shifts in real time and to find out the influence of Doppler frequency shift in RICE channel with two cases fading coefficients K = 4 and K = 16 to calculate CFO compensation. We conduct extensive simulations to evaluate the effectiveness of our proposed solution in high-speed railway environments.

The effectiveness of the automatic CFO compensation method is evaluated through BER value. The BER value after using the CFO compensation has decreased sharply, equivalent to the BER theoretical value. The results showed a substantial improvement in communication reliability and data integrity, with BER reductions confirming the effectiveness of the ML models. The method is suitable for the requirements of OFDM in LTE and in HSR communication. The results demonstrate a marked improvement in communication reliability and data integrity, highlighting the potential of machine learning to enhance the performance of mobile communication systems in high-speed railways.

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