Clustering-NN Based CFO Estimation Using Random Access Preambles for 5G Non-Terrestrial Networks

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***Abstract*—Non-terrestrial networks (NTNs) are expected to play a pivotal role in the future wireless ecosystem. Due to its high-dynamic characteristics, the accurate estimation and compensation of carrier frequency offset (CFO) are crucial for supporting 5G new radio (NR) enabled satellite direct access. With emphasis on ensuring reliable uplink synchronization, we propose a clustering-neural network based CFO estimation scheme by virtue of NR random access preambles. By leveraging the sparsity and regularity of input samples, the proposed scheme can achieve fast and precise prediction of CFOs, while establishing robustness against time uncertainty and channel variation within a satellite beam. Simulation results validate the feasibility of our scheme in various NTN scenarios, and demonstrate its superiority in terms of stable estimation performance over the existing schemes.**

***Index Terms*—Non-terrestrial networks, carrier frequency offset estimation, random access preamble, clustering, neural network.**

I. Introduction

To expand the coverage and services of terrestrial networks (TNs), the deployment of non-terrestrial networks (NTNs) has been regarded as a promising solution [1], given its capability of providing ubiquitous and continuous wireless connectivity. So far, the 3rd generation partnership project (3GPP) has been actively pushing forward the evolution of 5G new radio (NR) to support NTNs, and constantly delving into the new range of use cases, such as satellite direct access [2]. In this regard, one of the major challenges is how to address the impacts of characteristics of NTNs that are prominently distinguished from TNs on NR-based air interface transmissions [3]. In particular, large Doppler shifts caused by the fast movement of NT platform, e.g. low-earth-orbit (LEO) satellites, will result in dramatically increased carrier frequency offsets (CFOs), which severely degrades the performance of the orthogonal frequency division multiplexing (OFDM) waveform based NR uplink [4]. Therefore, it is essential to design an effective frequency alignment scheme to achieve multi-access orthogonality in high-dynamic NTN scenarios.

Towards this end, a potential solution is to pre-compensate CFO in advance by using its value estimated in downlink synchronization [5], [6], which, however, may lead to outdated and inaccurate CFO adjustment due to the rapid variation of NTN channels. A more reasonable alternative is to estimate the CFO directly by means of the reference signals in the NR uplink, e.g., random access (RA) preambles. Based on the conjugate symmetric Zadoff-Chu (CSZC) sequences [7], an integral CFO[1] estimation method was proposed for satellite communication system. In [8], two RA preamble sequences with different root indexes were concatenated to realize integral CFO estimation. However, the aforementioned approaches rely on the specific channel models and preamble formats, and moreover, they have to involve compensation strategy or cyclic prefix (CP)-based scheme [9] to mitigate the residual CFO. By contrast, the data-driven machine learning (ML) techniques are demonstrating increasing feasibilities in resolving synchronization issues, and neural networks (NNs) have been recently adopted for CFO estimation in OFDM systems [10], [11]. Nevertheless, the limited CFO estimation range and high implementation complexity will restrict their applications on board a payload-limited NR satellite receiver.

In this letter, we propose a clustering-NN based CFO estimation framework tailored for high-dynamic NTN scenarios by utilizing RA preambles. First, we design the selection principles of preamble root index to enable the relationship between power delay profile (PDP) of the received preamble and CFO unaffected by timing advance (TA) compensation errors and multipath effect. Then, by making full use of the sparsity and regularity of PDP samples, an efficient and lightweight CFO estimation model is further proposed. Specifically, a semi-supervised K-means clustering (SSKC) algorithm with initialization optimization is utilized for coarse estimation, while a sparse matrix dimension reduction (SMDR) based back propagation NN (BPNN) is constructed to achieve fine estimation. Simulation results demonstrate that our scheme can not only realize the estimation of both integral and

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[1] In OFDM systems, the CFO normalized by the subcarrier spacing can be divided into two parts, i.e. the integral CFO and the fractional CFO.

fractional CFOs, but is also capable of achieving significantly improved performance under various NTN channel models, in comparison to the benchmark schemes.

II. System Model

Due to the excellent correlation properties and low peak-to-average ratio, the ZC sequence has been adopted in 5G RA to generate preambles, which is defined as

$$s(n) \triangleq e^{-j\pi un(n+1)/N_{\text{ZC}}}, 0 \leq n \leq N_{\text{ZC}}-1 \tag{1}$$

where $u \in \{1, \ldots, N_{\text{ZC}}-1\}$ is the root index and N_{ZC} is the length of sequence. If a user attempts to access the network, it will select one of the available preamble sequences to transmit on the physical random access channel (PRACH). By passing over a satellite multipath fading channel, the received form of the preamble sequence is given as

$$y(n) = \sum_{l=1}^{L} h_l s(n-\tau-\tau_l) e^{-j2\pi\varepsilon n/N_{\text{ZC}}} + w(n), \tag{2}$$

where L, τ, and w represent the number of arriving paths, the round-trip delay, and the complex additive white Gaussian noise (AWGN), respectively, while h_l and τ_l are the gain and relative delay of the lth path. Note that in (2), ε is the normalized CFO, which can be expressed as $\varepsilon = f_d/\triangle f_{\text{RA}}$, where f_d denotes the Doppler shift, $\triangle f_{\text{RA}}$ denotes the subcarrier spacing (i.e. the reciprocal of the PRACH symbol duration). Also, it can be further given as $\varepsilon = \varepsilon_{\text{I}} + \varepsilon_{\text{F}}$, where $\varepsilon_{\text{I}} = \mathscr{R}(\varepsilon)$ ($\mathscr{R}(\cdot)$ denotes the rounding operation) and $\varepsilon_{\text{F}} \in (-0.5, 0.5]$ represent the integral and fractional parts of ε, respectively.

III. A ML-Based CFO Estimation Scheme

In this section, we present a ML-based CFO estimation scheme with assistance of RA preambles for NTNs. The proposed estimation scheme is based primarily on two findings: 1) PDP matrix is sparse and regular under the influence of CFO, and 2) using SMDR to remove redundant features can reduce the complexity of the NN while improving the accuracy of CFO estimation. Specifically, we describe the proposed scheme from the aspects of a robust preamble design and a clustering-NN based estimation model construction

A. Proposed RA Preamble Design

As a fundamental basis for user identification, PDP is usually computed by a periodical correlation between the received signal and each of available preamble sequences, which is given as

$$p(m) = \left| \frac{1}{N_{\text{ZC}}} \sum_{n=0}^{N_{\text{ZC}}-1} s^*(n) y[(n+m) \text{mod} N_{\text{ZC}}] \right|^2, 0 \leq m \leq N_{\text{ZC}}-1 \tag{3}$$

where $(\cdot)^*$ denotes the complex conjugate operation. To intuitively reveal the impact of CFO on PDP, we assume that τ can be effectively compensated before the preamble transmission, and the satellite channel model only contains the line-of-sight (LOS) path with gain $h_1 = 1$ [12]. In this case, the received signal in (2) can be expressed as

$$y(n) = s(n) e^{-j2\pi\varepsilon n/N_{\text{ZC}}} + w(n). \tag{4}$$

By substituting (1) and (4) into (3) and neglecting the noisy terms, $p(m)$ can be derived as

$$\begin{aligned} p(m) &= \left| \frac{1}{N_{\text{ZC}}} \sum_{n=0}^{N_{\text{ZC}}-1} e^{-j2\pi(um+\varepsilon)n/N_{\text{ZC}}} \right|^2 \\ &= \begin{cases} 1, & (um+\varepsilon) \text{mod} N_{\text{ZC}} = 0 \\ 0, & (um+\varepsilon) \text{mod} N_{\text{ZC}} = v \\ (\frac{1}{N_{\text{ZC}}} \frac{\sin[j\pi(um+\varepsilon)]}{\sin[j\pi(um+\varepsilon)/N_{\text{ZC}}]})^2, & \text{otherwise} \end{cases} \end{aligned} \tag{5}$$

where $v \in \mathbb{Z}$ and $v \neq 0$. It can be found from (5) that when ε is an integer, i.e. $\varepsilon = \varepsilon_{\text{I}}$, there exists only one correlation peak at the time index of $(-\varepsilon_{\text{I}}/u) \text{mod} N_{\text{ZC}}$ in PDP. On the other hand, if $\varepsilon = \varepsilon_{\text{I}} + \varepsilon_{\text{F}}$ and $\varepsilon_{\text{F}} \neq 0$, the maximum correlation peak of PDP does not shift, but several false peaks appear at the multiple times of $(-1/u) \text{mod} N_{\text{ZC}}$. Hence, *the PDP vector is sparse and regular in the presence of CFO.* Based on this feature, an efficient feature extraction can be deployed in advance of the NN design to project the PDP vector to a low-dimensional one, which is conducive to simplifying the number of nodes in the input layer of the NN.

However, due to the inaccurate TA compensation and multipath effect, namely time uncertainty, in the practical NTN scenarios, the PDP peaks corresponding to different CFOs may be indistinguishable from each other, resulting in an obvious performance degradation of network prediction. To solve this problem, we propose two principles for the root index selection of preamble sequences, listed as follows:

1) u is a prime number.
2) For arbitrary $\varepsilon_1, \varepsilon_2 \in \mathcal{E}$ and $\mathscr{R}(\varepsilon_1) \neq \mathscr{R}(\varepsilon_2)$, $|(-\mathscr{R}(\varepsilon_1)/u) \text{mod} N_{\text{ZC}} - (-\mathscr{R}(\varepsilon_2)/u) \text{mod} N_{\text{ZC}}| > 2T_{max}$.

Here, $\mathcal{E} = [-\varepsilon_{max}, \varepsilon_{max}]$ denotes the range of normalized CFOs that can be determined in an actual NTN scenario and ε_{max} is the maximum value of normalized CFO, while T_{max} represents the maximum value of time uncertainty.

In order to demonstrate the necessity of the proposed principles, we consider the scenario referred to as $D2$ from the NTN reference scenarios provided by 3GPP [13], wherein the LEO satellite is placed at an altitude of 1200 km. In this scenario, the high-speed movement of satellite can lead to a Doppler shift of up to 21 ppm, which is equivalent to 42 kHz at a carrier frequency of 2 GHz. Then, we adopt the PRACH Format 3 [14] with $\triangle f_{\text{RA}} = 5$ kHz and $N_{\text{ZC}} = 839$ to construct RA preamble, thus ε_{max} is calculated as 8.4 and $\mathcal{E} = [-8.4, 8.4]$. Given that the maximum time uncertainty $T_{max} = 8$, we can obtain all the root indexes that satisfy the proposed principles, among which the minimum one is 17. For clarity, we illustrate the PDPs under different normalized CFOs in Fig. 1, where NTN-TDL-B [15] model is used as the channel model, and the signal-to-noise ratio (SNR) is set as 20 dB. It is notable that, for the root index $u = 7$ that does not satisfy the second principle, the interval between the peak positions of PDPs corresponding to $\varepsilon = 3.3$ and $\varepsilon = -4.3$ is only one time lag, which may result in a wrong estimation result by considering the delay spread of the channel. Nevertheless, this problem can be resolved by the constrained design of the root indexes in the proposed principles, thereby guaranteeing the correspondence between PDP and CFO unaffected by the time uncertainty. Furthermore,

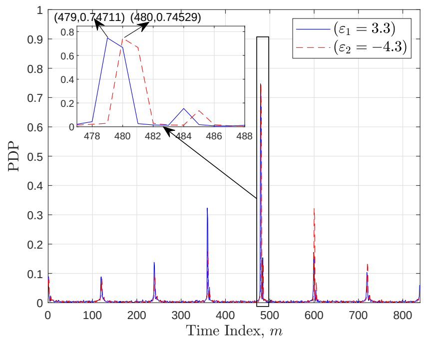


Fig. 1. PDPs under different normalized CFOs for $u = 7$.

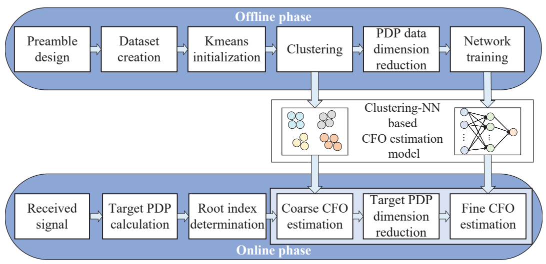


Fig. 2. Framework of proposed CFO estimation scheme.

by exploiting different root ZC sequences to generate all the available preamble sequences, the access user identification can be achieved under various NTN channel models.

B. Proposed Clustering-NN Based CFO Estimation Model

In the following, we further propose a clustering-NN based model for accurate CFO estimation in high-dynamic NTN scenarios, by using a SSKC algorithm and a SMDR-optimized BPNN. The framework of the proposed scheme is shown in Fig. 2, which includes two phases, namely offline training phase and online testing phase. At the offline phase, PDP samples are generated by using all the available preamble sequences based on the proposed principles. Then, an estimation model is constructed by SSKC-BPNN, wherein SSKC performs coarse estimation to find out the nearest integer to CFO, and BP module further extracts and learns the features hidden in the samples to estimate the accurate value of CFO. At the online phase, the valid root indexes are first determined by the captured correlation peaks in PDP calculation, and the offline trained model is subsequently used to realize the CFO estimation online for each of root indexes.

1) Dataset: The dataset is created from the PDP samples of available preamble sequences across the normalized CFO range of $\mathcal{E}$ with resolution of η, which is expressed as

$$\mathcal{D} = \{(\mathbf{p}_g, \varepsilon_g) | g = 1, ..., G\}, \tag{6}$$

where $\mathbf{p}_g$ denotes the gth PDP sample with N_{ZC} features, ε_g denotes the label of $\mathbf{p}_g$, and G is the size of the dataset. Specifically, we adopt the same scenario and preamble format as in Fig. 1 to build the dataset, and η is set to be 0.001. In this way, $\mathcal{E}$ becomes $[-8.400, -8.399, ..., 0, ..., 8.399, 8.400]$ with length of $((2 \times 8.4)/0.001 + 1 = 16801)$, featuring both integral and fractional CFOs. To further enhance the feasibility of network model in high-dynamic satellite environments, PDP samples under different NTN channels are collected into the dataset, including AWGN, NTN-TDL-B and NTN-TDL-D [15] (as detailed in Table I and Table II). For each channel model, we randomly create 100 PDP samples per CFO value in $\mathcal{E}$, resulting in a total of $G = 5040300$ samples in $\mathcal{D}$. From the dataset, 70% of the samples are used for training, while the remaining 30% are used for testing. Moreover, in order to accelerate the convergence of the model, we compress the sample values of PDP into the range of $[0, 1]$.

TABLE I
NTN-TDL-B CHANNEL MODEL

Tap #	Normalized delay	Power in [dB]	Fading destributing
1	0	0	Rayleigh
2	0.7249	-1.973	Rayleigh
3	0.7410	-4.332	Rayleigh
4	5.7392	-11.914	Rayleigh

TABLE II
NTN-TDL-D CHANNEL MODEL

Tap #	Normalized delay	Power in [dB]	Fading destributing
1	0	-0.284	LOS path
1	0	-11.991	Rayleigh
2	0.5596	-9.887	Rayleigh
3	7.3340	-16.771	Rayleigh

2) SSKC-Based Coarse Estimation: Next, we investigate how to achieve a rough estimation of CFO for each PDP sample in $\mathcal{D}$. It can be found from Fig. 1 and (5) that, the maximum peak of PDP decreases in the presence of ε_{F}, but its position does not change. Hence, the features of PDP samples possess similarity in a certain range of CFO, such that *the coarse CFO estimation can be converted into a clustering problem*. Given the regularity of PDP samples and for better construction of NNs, we pursue that each data sample can belong to only one cluster after clustering, and thus we adopt the K-means clustering algorithm in this work. Note that, if the initialization is randomly selected, the clustering performance of K-means can not be always guaranteed [16]. Different from the existing works that proceed initialization optimization at the expense of complexity, e.g. K-medoids and kernel K-means, we propose a SSKC algorithm based on the features of input data, which takes the regularity of PDP as prior knowledge to guide the clustering process, thus can lead to a more reasonable data classification.

In particular, we set the number of integral CFOs in $\mathcal{E}$ as the K-value, and take their PDP samples as the initial clustering centers, and the clustering process will be completed until the iteration termination condition is reached. At the online stage, the target data cluster $\hat{k}$ is obtained by calculating the Euclidean distance of the positions of maximum peaks, i.e.

$$\hat{k} = \arg\min_{k} \sqrt{(x_1 - x_k)^2 + (n_1 - n_k)^2}, k \in [1, K] \tag{7}$$

where (x_1, n_1) and (x_k, n_k) denote the positions corresponding to maximum peaks of the target PDP and the kth clustering center, respectively. After clustering, the coarse CFO estimation for each of target samples can be implemented at the online phase.

3) SDMR-BPNN Based Fine Estimation: On account of the limited payload of satellite receiver, we further resolve the fine CFO estimation problem with the aid of BPNN, which has the advantages of low complexity and fast model training [17]. According to the clustering results, the PDP samples in each of categories are used to train a BPNN. Since a network with fewer layers can realize arbitrary nonlinear mapping in case of unrestricted number of nodes of the hidden layer [18], we employ a one-hidden-layer BPNN in this work.

As shown in Fig. 2, each layer of BPNN consists of multiple neurons, whose output is a nonlinear function of a weighted sum of neurons of its preceding layer, which is described as

$$\mathbf{Z}^j = \mathscr{F}^j\left(\mathbf{W}^j \mathbf{Z}^{j-1} + \mathbf{b}^j\right), \tag{8}$$

where $\mathbf{Z}^j$, $\mathbf{W}^j$, $\mathbf{b}^j$ denote the output, weights, and thresholds of the jth layer for $j = 1, 2, 3$, respectively. $\mathscr{F}^j(\cdot)$ denotes the transfer function of the jth layer, and is uniformly set to be $\mathscr{F}(x) = 2(1 + e^{-2x})^{-1} - 1$ here. To adapt the weights and thresholds to different inputs, the BPNN tries to find the residual CFO, i.e. $\hat{\varepsilon}_{\mathrm{F}}$, that minimizes the loss function E, which is defined as

$$E = \frac{1}{G_k} \sum_{i=1}^{G_k} (\varepsilon_{\mathrm{F}} - \hat{\varepsilon}_{\mathrm{F}})^2, \tag{9}$$

where G_k is the number of samples in the kth cluster after the clustering process. Based on the aforementioned settings, the offline training is performed by using the BP algorithm and G_k samples until E is below a certain threshold or the number of iteration terminations is reached, and the trained BPNN can be exploited for the fine CFO estimation at the online phase.

However, the BPNN is fully-connected between the adjacent layers, and consequently its complexity is proportional to the number of neurons in each layer. We denote the number of nodes in the hidden layer as H, and adjust its value by combining with the empirical formula, which is given by

$$H = \lfloor \sqrt{C + O} \rfloor + A, \tag{10}$$

where C represents the number of nodes in the input layer, i.e. N_{ZC}, O is the number of nodes in the output layer and is equal to 1, A is a constant in the range of $[1, 10]$. Note that in (10), C and H depend on the number of features of data that is an N_{ZC}-dimensional vector, however, such high-dimensional feature vector increases the complexity of the network model and the difficulty of training. Actually, only few features of a PDP sample are affected by the CFO, the rest of features are mostly noise related, which contribute nothing to the target output and may even worsen the estimation performance of the network. By considering this fact, we attempt to reduce the feature space dimension by extracting a subset of non-redundant features, so as to improve accuracy and training time of the network model.

By utilizing the sparsity of PDP in (5), we propose to extract the sensitive features at the multiple times of $(-1/u)\mathrm{mod}N_{\mathrm{ZC}}$ from each of samples. Specifically, we construct an indicator vector of peak position, denoted as $\mathbf{q}_u \in \mathbb{R}^{N_{\mathrm{ZC}} \times 1}$, for each of the available root indexes. If the position is the multiple times of $(-1/u)\mathrm{mod}N_{\mathrm{ZC}}$, the element at that position is recorded as 1, otherwise it is equal to 0. Then, Hadamard product operation is performed by $\mathbf{q}_u$ and each of PDP samples, i.e.

$$\mathbf{p}_g' = \mathbf{q}_u \circ \mathbf{p}_g, \tag{11}$$

where $\mathbf{p}_g'$ is the converted sparse PDP sample. By leveraging the non-zero values of $\mathbf{p}_g'$ to reconstruct sample, the dataset can be correspondingly reduced to a low-dimensional matrix through the above SMDR process. In this way, the impact of redundant features on the original dataset is effectively removed, allowing the proposed model to focus more on the sensitive features and reduce the reliance on invalid information. As a result, the enhanced BPNN can learn data features faster and more accurately to establish the relationship between input and output, leading to a better fine CFO estimation performance online.

TABLE III
PARAMETERS AND SETTINGS

Parameters	Values
Sequence length, N_{ZC}	839
PRACH subcarrier spacing, $\triangle f$	5 kHz
Maximum time uncertainty, T_{max}	8
Root index, u	17
Resolution, η	0.001
Range of normalized CFOs, $\mathcal{E}$	[-8.4, 8.4]
Number of clusters, K	17
Number of hidden nodes, H	5
Signal-to-noise ratio (SNR)	20 dB
Channel models	{AWGN, NTN-TDL-B/D}

IV. Performance Evaluation

In this section, computer simulations are conducted to assess the performance of the proposed scheme, and the data generation and SSKC-BPNN model parameters are listed in Table III. Here, the channel models in the simulations are consistent with those in the dataset, and one OFDM symbol in PRACH preamble with Format 3 is used for CFO estimation. According to the proposed design principles, we can obtain all the available root indexes independent of the time uncertainty, and choose one of them in the simulation for convenience.

We show the performance of coarse estimation with different clustering algorithms under AWGN channel in Fig. 3, where success prediction probability (SPP) is adopted as the criterion and ε_{I} are set as -3, 1, 3, respectively. Note that, the SPP of K-means remains relatively small value under arbitrary SNR conditions, while our proposed SSKC with initialization optimization, which considers the regularity of input data, achieves perfect prediction performance for various CFOs as SNR ≥ -15 dB. This demonstrates that the adoption of data features as the prior knowledge can effectively improve the performance of clustering.

Fig. 4 depicts the mean square error (MSE) curves of BPNN-based fine estimation under various normalized CFOs, ε, wherein the SNR is set to be 20 dB. It is observed that the BPNN-based schemes can obtain stable MSE performance across the entire estimation range, which is attributed to the fact that BPNN with the exceptional nonlinear fitting capability is able to establish precise input-output relationship by extracting features from extensive data. Furthermore, by retaining valuable information and resisting interference of redundant features during the dimension reduction process, the proposed SMDR-BPNN apparently lowers network complexity and enhances the accuracy of CFO estimation. Besides, a better estimation performance can be achieved with the expansion of the dataset. It is also shown that our scheme is

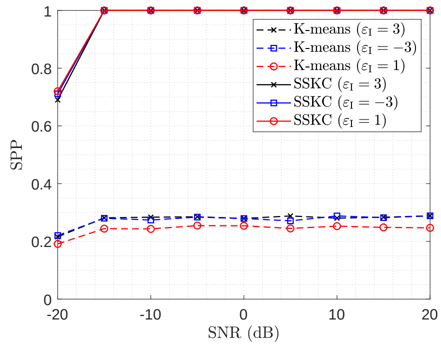


Fig. 3. SPP performance of coarse estimation under various SNRs.

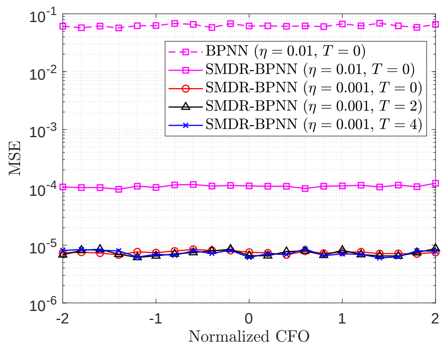


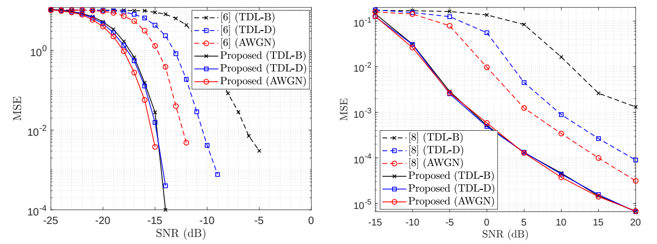
Fig. 4. MSE performance of fine estimation under various CFOs.

capable of possessing the robustness to various timing offsets, since the influence of time uncertainty has been eliminated by the proposed principles.

To reveal the feasibility of the proposed scheme in high-dynamic NTN scenarios, we show the impacts of different channel models on CFO estimation performance of the proposed scheme in Fig. 5, where the CSZC sequences-based integral CFO estimation scheme [7] and CP-based fractional CFO estimation scheme [9] are adopted as benchmarks for comparison. It can be found that the proposed scheme can have evidently enhanced estimation accuracies under various channel conditions, and the performance gain becomes larger with the degree of the channel dispersion. The significant performance improvement comes from the elaborate root index selection principles as well as the denoising and adaptive capabilities of the proposed clustering-NN model, robustifying our estimator against channel variations. Also, it is proven that the proposed scheme can achieve the complete CFO estimation when both integral and fractional CFOs exist, as compared to the existing ones.

V. Conclusion

In this letter, we proposed a clustering-NN based CFO estimation scheme for 5G NTNs. Since the proposed scheme is able to optimize the performance with reduced complexity by leveraging the unique characteristics of PDP samples, it is suitable for payload-limited satellite receiver while ensuring a high accuracy of CFO estimation. Simulation results revealed the superiority of our scheme in terms of the MSE, SPP, and the robustness to channel models, compared with the previous ones. Furthermore, it can also be exploited for ZC sequences based frequency synchronization of other OFDM systems. In the future, we plan to extend our work to investigate the impact of different network models on the accuracy of CFO estimation, such as convolutional NN.



(a) Integral CFO estimation (ε=1) (b) Fractional CFO estimation (ε=0.3)

Fig. 5. Performance comparison of different estimation schemes under various channel models.

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