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Deep Learning Based AI Model for Improving Carrier Frequency Offset Estimation in Sensor Driven Communication Systems

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Abstract

Carrier frequency offset (CFO) represents one of the most significant issues when it comes to wireless networks and sensor systems (communication) that occur due to mismatches of oscillators and the Doppler shifts that arise because of user mobility. These variations can disrupt signal synchronization, so communication and security in wireless ad hoc and sensor networks can be seriously affected. Determining the CFO accurately and reliably is the foundation of the safety of the whole system. This work digitally announces a neural network-based method (deep learning) that merges Bidirectional Long Short-Term Memory (BiLSTM) with Convolutional Neural Networks (CNN) in order to estimate CFO from the corrupted Zadoff-Chu (ZC) sequences. The proposed network can make an estimation of the CFO with a very small error rate, even under signal conditions with a low signal-to-noise ratio (SNR). In the experiments, the proposed scheme raises the level of performance beyond the classical techniques. The proposed model's Mean Absolute Error (MAE) at various SNR levels is lower than that of traditional methods. At 10 dB, MAE is 13.02 Hz for the proposed model as compared to 17.44 Hz for CNN, and 21.22 Hz for LSTM. Besides this, the model at low SNR conditions (0-5 dB) dramatically reduces the error margin, hence it is very quiet in a noisy environment. The main performance metrics for this work are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and regression correlation coefficient (R). All these parameters reflect the superior performance of the proposed method when implemented in real-time for sensor-driven networks.

Keywords: Carrier Frequency Offset (CFO), Wireless Communication, Signal Synchronization, Deep Learning, Bidirectional Long Short-Term Memory (BiLSTM), Convolutional Neural Networks (CNN), Zadoff-Chu (ZC) Sequences, Sensor Networks.

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1 Introduction

In real wireless communication systems, the oscillators that are utilised between transmitter and receiver cannot achieve good synchronization due to hardware imperfections and environmental conditions (Alabd et al., 2022; Kazeminezhad, 2015). This variance produces a significant carrier frequency offset (CFO), which damages the frequency alignment between the transmitter and receiver. As a result, the performance of coherent demodulation deteriorates rapidly, leading to unreliable communication and a substantial decline in overall system efficiency. Consequently, precise estimation and adequate compensation of the CFO are essential for maintaining the integrity and reliability of modern communication systems.

Synchronization in the current wireless communication systems is essential, especially in wireless ad-hoc and sensor networks, in order to preserve the integrity and security of the data (Moslehi, 2025). Carrier frequency offset (CFO) is an important parameter that can have dire consequences on the performance of the system, particularly when dealing with environments that are likely to cause oscillator mismatch and Doppler shift due to mobility. Synchronization errors not only negatively impact the quality of communication in such networks but also put transmitted data at high risk. The CFO estimation, hence, becomes a significant responsibility in ensuring the integrity of these systems as well as their security (Nguyen et al., 2025). The paper presents a new deep learning model that comprises Bidirectional Long Short-Term Memory (BiLSTM) and Convolutional Neural Networks (CNN), which is developed to predict CFO using distorted Zadoff-Chu (ZC) sequences in real-time applications, thereby maintaining robust communication and enhanced security in sensor-driven networks (Fang et al., 2022; Nakano & Nishimura, 2021).

CFO estimation approaches are categorized into two primary techniques: non-data-aided (NDA) and data-aided (DA) approaches (Champion et al., 2019). The DA models utilise signal sequences to predict the frequency offset. Mainly, DA approaches have been applied for carrier burst transmission systems. Recently, several methods, such as the autocorrelation method and the maximum likelihood method, have been designed for reducing computational time and achieving accurate estimation results. Although the results showed promise in CFO estimation, the methods are more vulnerable to interference and noise, offering inadequate resistance against such disruptions. In this regard, NDA based approaches for CFO estimation have been adopted in various communication applications. NDA models depend on the received signal. As a result, NDA models provide quick and more accurate frequency offset estimation.

With the rapid advancement of machine learning and deep learning approaches, these technologies have been widely employed in various applications such as time series prediction, and image and signal recognition (Giji Kiruba et al., 2023; Goodfellow et al., 2016). Deep learning techniques simulate the intricate neural approach of the human brain, allowing it to process massive volumes of data and pullout practical features (Durga & Sudhakar, 2015). These extracted features are then used to tackle classification or regression issues (Dai et al., 2020; Al-Dawoodi et al., 2019). Recently, deep learning-based approaches have attracted significant attention in detecting attacks, signal modulation, and network investigations. Similarly, a deep learning base approach has also been applied in the CFO estimation, for example, a study in applied deep neural networks to estimate CFO (Manea et al., 2025; He et al., 2016). The focus was on the CFO of receiving orthogonal frequency-division multiplexing (OFDM) signals. Another study integrated a convolutional neural network with an attention mechanism to predict CFO values of OFDM signals (O'Shea et al., 2016). To evaluate the model's effectiveness, to evaluate the model's effectiveness, extensive experiments are performed using synthetic datasets generated from Zadoff-Chu sequences with frequency, phase, and time distortions, corrupted by additive

Gaussian noise. Performance is assessed using root mean square error (RMSE), mean absolute error (MAE), and regression correlation coefficient (R). The findings show that it has a considerable improvement over the baseline techniques, both in accuracy and strength.

The paper has made contributions, which can be summarized as follows:

1. The CNN-BiLSTM model is created that integrates the learning of convolutional features along with the features that are learned in time to predict CFO.
2. A pipeline of feature extraction is also built to obtain various representations of the distorted signal, such as FFT spectrum, statistical moments, and IQ phase measures.
3. It is shown that the model is able to learn and generalize on noisy and distorted signals on a synthetic testbed on realistic wireless impairments.
4. Quantitative tests are presented at various levels of SNR, and the performance of the models is compared to the conventional benchmarks.

The rest of the paper is organized as follows: Section 2 reviews related work. Section 3 presents the methodology, including signal modelling, feature design, and model architecture. Section 4 details the experimental setup and training procedure. Section 5 provides results and analysis. Finally, Section 6 concludes with future directions.

2 Related Work

The estimation of carrier frequency offset has received a lot of research in wireless communication because of its direct influence on the performance of the demodulation process (Ait Aoudia & Hoydis, 2018; John et al., 2024). The primary methods in traditional techniques are those that are based on maximum likelihood (ML), exploitation of the cyclic prefix, and phase-locked loops (PLLs). These techniques, though analytically tractable, are typically based on idealistic assumptions, e.g., Gaussian noise, linear distortion models, and correct pilot sequences. These assumptions do not hold in real situations that are characterized by multipath, Doppler, and imperfect oscillators, and the effects result in severe deterioration of performance.

ML-based estimators, such as those, have been known to be optimal when there is white Gaussian noise, but are computationally exhaustive to calculate, especially when the CFO search space is ample. PLLs are tracking capable but cannot withstand initial estimates of the frequency offset and do not work well in highly dynamic channels (Cowley, 2002). FFT-based estimators, which are frequently employed in OFDM systems, depend on the structure of cyclic prefixes but are vulnerable to noise and inter-symbol interference (ISI).

In order to overcome these shortcomings, data-based techniques have emerged (Ait Aoudia & Hoydis, 2018). Some current studies examine how machine learning models can be used in signal processing applications such as channel estimation, modulation classification, and CFO detection. Deep learning in classifying the OFDM signal at various conditions of the channel (Almayyali & Hussain, 2021). Equally, a timing and frequency synchronization estimator based on a neural network performed better than classical methods in the presence of an extreme number of multipath distortions.

The hybrid deep learning architectures have become popular in recent years as well (Veit et al., 2016). An example is the use of CNNs in spectrum analysis and signal classification, and LSTM-based models in the modelling of long-term signal dependence. Very little literature has been done to incorporate these models in the context of CFO estimation. This method is unique in that it uses a CNN-BiLSTM architecture to co-model spectral and temporal characteristics obtained using Zadoff-Chu sequences.

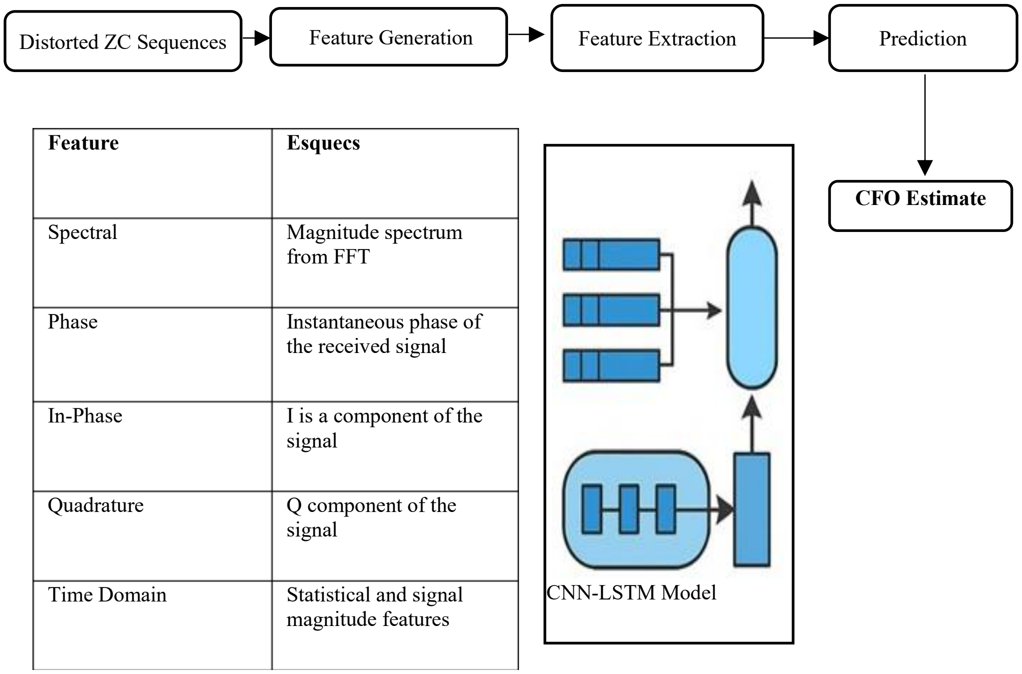
The other direction of the research that may be considered is the Zadoff-Chu use in synchronization. The deterioration in the ZC properties when under CFO and suggested compensatory algorithms. Nevertheless, these solutions tend to be heuristic, and they are not adaptable to various distortion conditions.

Conversely, the approach has an intense feature extraction phase and a learnable model that learns directly from data without any assumptions about the underlying distortion process. This is due to the integration of convolutional filters, which boosts the recognizability of spatial patterns of frequency features by the model, and the BiLSTM learns long-term dependencies influenced by time and phase shifts.

Overall, even though the classic estimators and the newly developed machine learning tools have solved the CFO estimation to some extent, the suggested CNN-BiLSTM model is a new and unified model that suits distorted ZC sequences amid noisy conditions. The methodology contributes to the state of the art through the fusion of a wide range of signal characteristics into a scalable system of deep learning (Meymari et al., 2015).

3 Methodology

Figure 1 depicts the proposed model for CFO. In this paper, several features are extracted to estimate the CFO. Then, the extracted features are sent to design a CNN with a BiLSTM model. The features are extracted from distorted Zadoff-Chu sequences.



Feature	**Esquecs**
Spectral	Magnitude spectrum from FFT
Phase	Instantaneous phase of the received signal
In-Phase	I is a component of the signal
Quadrature	Q component of the signal
Time Domain	Statistical and signal magnitude features

Figure 1: The proposed model for off-site estimation

3.1 Signal Generation

A synthetic dataset is generated using distorted Zadoff-Chu (ZC) sequences to evaluate the performance of the proposed model for CFO estimation. The use of ZC sequences in communication systems is primarily based on the ideal constant amplitude and autocorrelation characteristics of the sequences, which allow the sequences to be resistant to synchronization errors. The base signal in this research was taken to be a ZC sequence with a length of 256. To replicate a real-world wireless communication situation, the sampling frequency was adjusted to 1 MHz.

The generated dataset contains a total of 20,000 samples. The dataset is divided into a training set of 80% and 20% for a testing set of 20%. The generated signals were distorted by applying a random frequency offset uniformly chosen from the range of −500 to +500 Hz. The frequency offset was modelled using a complex exponential term, and an additive white Gaussian noise (AWGN) was added at an SNR level of 10 dB. These conditions were selected to emulate realistic noise environments. The distorted signals were filtered by a raised cosine transmit filter with eight samples per symbol and a span of 10 symbols. A zero-phase offset condition was considered for all simulations. The final IQ samples were pulled out as real and imaginary parts of the first 256 symbols post-filtering.

3.2 Feature Extraction

I-Q: One of the critical features for signal characterisation and detection in modern communication applications is the In-phase (I) and Quadrature (Q) components of a complex baseband signal. These features depict the complete phase and amplitude information of waveforms, making the features essential for data-driven learning tasks such as carrier frequency offset (CFO) prediction. In this study, the received Zadoff-Chu sequence is transformed into a matrix of 2xN length, where N refers to the sequence length, and the number 2 corresponds to the real (I) and imaginary (Q) parts of the signal, respectively. This depiction effectively extracts the temporal and spectral components of the signal, enabling a deep learning model to extract localized patterns and non-linear relationships. The baseband signal $s(t)$ is expressed as:

$$s(t) = I(t) + jQ(t) \qquad (1)$$

In equation 1, where $\mathrm{I}(t) = \Re(s(t))$ and $Q(t) = \Im(s(t))$. These features are extracted for each signal and formed into a 2D tensor, which is used as an input to the proposed model. Through this IQ-based formulation, the network can learn the frequency shifts, phase rotations, and amplitude variations that are caused by channel impairments: noise, Doppler shift, and multipath. The combination of I and Q in joint modelling, therefore, gives a complete picture of the signal, which allows a strong and precise prediction of the CFO even when the signal-to-noise ratio is low.

- **FFT Features (50 Features)**

The Fast Fourier Transform (FFT) is a handy tool in the analysis of the spectral properties of time series data. In the context of CFO estimation, analysing the spectral components of the CFO signal is essential for detecting frequency shifts produced by synchronization errors. In this paper, A total of 50 characteristics from the centered magnitude spectrum (via FFT-shift) are adopted to extract the most significant spectral components. The main formula to extract the spectral components is expressed as**:**

$$X_{FFT} = |FFT_{shift}(r[n])| \qquad (2)$$

In equation 2, where $r[n]$ refers to the received signal. The first 50 bins from the magnitude of the FFT_{shift} are extracted to estimate the CFO.

- **Statistical Features**

In this paper, four statistical features are extracted from the real part of the signal. These features depict signal shape, energy dispersion, and randomness, which are sensitive to CFO. The list of the statistical features extracted is described below:

Mean: $min = \frac{1}{N}\sum_{i=1}^{n} X(x_i)$ (3)

Variance: $var = \frac{1}{N}\sum_{i=1}^{n}(X(x_i) - \min)^2$ (4)

Skewness: $Skw = \frac{1}{N}\sum(\frac{X(x_i)-\min}{var})^3$ (5)

Kurtosis: $Kurt = \frac{1}{N}\sum(\frac{X(x_i)-\min}{var})^4$ (6)

Equation (3) to (6) gives the statistical measures of signal analysis. Equation (3) computes the mean (min), which is the mean of all the signal values. Equation (4) represents the variance (var), which is a measure of the dispersion of the signal about the mean. In Equation (5), the skewness (Skw) is calculated, and it shows how the signal is asymmetrical. The calculation of the kurtosis is found in Equation (6), which is the tailed Ness of the distribution. The action would assist in the decision-making of signal characteristics, which is necessary in estimating the CFO.

Normalisation

Numerous features with different scales were extracted to estimate CFO. Using different scale features can degrade the model performance and slow the convergence process. To solve this issue, the extracted features were normalized by scaling to a standard range using the Min-Max Normalization approach. This centres the data and gives it unit variance.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{7}$$

In equation 7, where x denotes the original feature, x_{max} *and* x_{min} are the max and min values of the extracted features.

3.3. Convolutional Neural Network (CNN)

The convolutional neural network (CNN) was designed to process 1-D and 2-D data such as images and time series data. The use of 1D-CNN is achieving popularity due to its strong ability to extract features compared to other machine learning models [25], which is also employed for CFO estimation in this work. CNN model can extract the temporal dependencies and spatial locality of CFO, which is especially crucial to estimate CFO. In this work, a CNN network is used to process the 67-dimensional feature vectors extracted from distorted Zadoff-Chu sequences.

The convolution operation is defined as:

$$y_i^l = f(\sum_{n=1}^{N} w_n^l x_i + n - 1 + b^l \tag{8}$$

In equation 8, where x is the input feature vector, w_n^l are the kernel weights at layer l, b^l refers to the bias term, f denotes the activation function (ReLU), and y_i^l is the output at index i.

Bidirectional Long Short-Term Memory (BiLSTM)

An LSTM model is a type of recurrent neural network that is designed to learn long-term dependencies in sequential time series data. With CFO estimation, temporal dependencies among phase, frequency, and statistical features can significantly improve estimation accuracy.

The core LSTM is defined as:

$$ft = \sigma\left(W_f x_t + U_f h_{t-1} - 1 + b_f\right) \quad (9)$$

$$i_t = \sigma(W_i x_t + U_i h_t - 1 + b_i) \quad (10)$$

$$c_t = \sigma(W_c x_t + U_c h_t - 1 + b_c) \quad (11)$$

$$o_t = \sigma(W_o x_t + U_i h_t - 1 + b_o) \quad (12)$$

$$h_t = o_t \odot \tanh c_t \quad (13)$$

The basic operations of an LSTM model are described by the equations (9) to (13), in which Equation (9) is referred to as the forget gate (f t) and defines how to retain the previous hidden state, Equation (10) describes the input gate (i t) and illustrates how the new information is added to the cell state, and Equation (11) updates the cell state (c t). Equation (12) is the output gate (o t) and determines the output according to the state of the cell, and the final production hidden state (h t) is calculated in Equation (13). As illustrated in Equation (14), the BiLSTM operates both forwards and backwards, thus allowing the model to obtain both past and future dependencies and therefore is the best model to be used to model the non-linear trends in CFO estimation.

A Bidirectional LSTM (BiLSTM) extends the version of LSTM by processing the sequence in both forward and backward directions:

$$h_t^{bi} = [\overrightarrow{h_t}, \overleftarrow{h_t}] \quad (14)$$

Equation 14 allows the model to learn both future and past dependencies, making it especially useful for modelling the non-linear trends in CFO.

Algorithm 1: End-to-End Workflow for Carrier Frequency Offset (CFO) Estimation using CNN-BiLSTM

Input:

- *$D = \{X, Y\}$: Training dataset with inputs X(distorted Zadoff-Chu sequences) and labels Y(true CFO values)*
- *$\theta = \{W, B\}$: Neural network weights and biases for CNN and BiLSTM models*
- *η: Learning rate for model optimization*
- *T: Number of training epochs*
- *λ: Regularization factor for the model*

Output:

- *Trained model $\theta$for accurate CFO estimation in wireless sensor networks*

Pseudocode:

```
1. Initialize model parameters $\theta = \{W, B\}$ and feature extraction functions
2. For each epoch $t = 1$ to $T$:
```

```
    a. For each training sample $(x, y) \in D$:
        i. Extract features from x (IQ components, FFT, statistical features)
        ii. Pass extracted features through the CNN model to extract spatial features
        iii. Process CNN output through BiLSTM model to capture temporal dependencies
        iv. Apply fully connected layers for the final CFO prediction
        v. Compute prediction error:
            - Loss = MeanSquaredError (predicted_CFO, true_CFO)
    b. Compute regularization loss for the model parameters:
        i. L_regularization = $\lambda * ||W||^2$        # L2 regularization for weights
    c. Compute total loss as:
        i. L_total = Loss + L_regularization
    d. Update model parameters via backpropagation:
        $\theta \leftarrow \theta - \eta * \nabla\theta$ L_total
3. End For
4. Return trained model $\theta$ that provides accurate CFO estimation for real-time wireless networks
```

The CNN-BiLSTM model in the form of the CFO Estimation Algorithm 1 is meant to estimate the Carrier Frequency Offset (CFO) in a wireless sensor network. The following is a breakdown of each component within the algorithm, and is intended to handle the distorted Zadoff-Chu sequences, and will give the correct predictions of the CFO. The algorithm incorporates the use of Convolutional Neural Networks (CNN) to acquire spatial features and the Bidirectional Long Short-Term Memory (BiLSTM) networks to acquire temporal dependencies.

3.4 Combined CNN-BiLSTM with Dense Layers

The proposed hybrid CNN-BiLSTM model combined the advantage of CNNs to extract spatial features and the strength of LSTM in modelling temporal dynamics. Figure 2 depicts the proposed model. The combination is structured as follows:

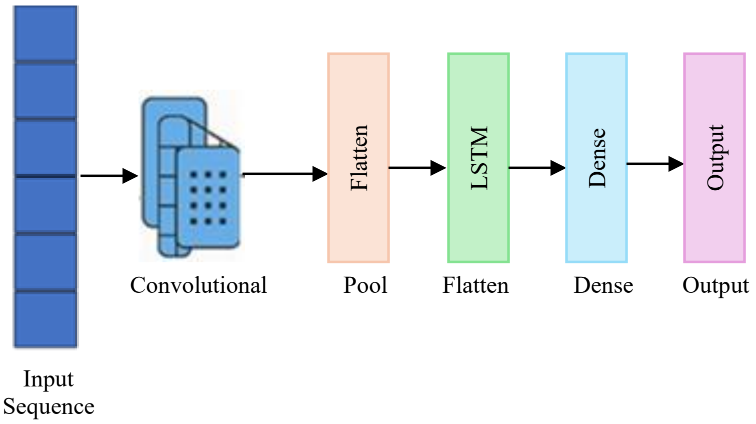


Figure 2: The designed CNN-LSTM model

1. **Input Layer**: received the reshaped feature vector.
2. **CNN Layers**: pulls out local signal patterns using 2D convolutional layers with the feature dimension.
3. **Squeeze Layer**: transferred the 4D CNN output to a 2D form acceptable by BiLSTM.
4. **BiLSTM Layer**: Captures bidirectional dependencies in the sequential features.
5. **Dense Layers (Fully Connected)**:
    a. First dense layer (64 units + ReLU) learns a high-level feature representation.
    b. Final dense layer (1 unit) performs scalar **regression** for frequency offset prediction.

The final output is given by:

$$\hat{y} = W_{des}^{2} \,.\, RELu(W_{des}^{1} . h_{bilstm} + b^{1}) + b^{2} \qquad (15)$$

In equation 15, where h_{bilstm} is the output from the BiLSTM, W_{des}^{2}, W_{des}^{1} are dense layer weights, and b^{1}, b^{2} are bias vectors, $\hat{y}$ denotes the predicted frequency offset.

4 Results and Discussion

All experiments, deep learning, feature extraction and simulation of signals were done in MATLAB (R2022a). Synthetic generation of distorted Zadoff-Chu sequences was done to simulate realistic carrier frequency offset as well as noise conditions. The processing of signal processing, such as the calculation of FFT, I/Q decomposition, statistical feature extraction, and feature normalization, were done through the Signal Processing Toolbox of MATLAB. The CNN -BiLSTM model was implemented, trained, and assessed through the MATLAB Deep Learning Toolbox. The standard regression measures like RMSE, MAE and correlation coefficient were used to evaluate the model performance. Each of the experiments was done under a controlled software environment in order to guarantee high levels of reproducibility and consistency in the results.

The proposed model was compared with the benchmark model in terms of the Mean Absolute Error (MAE), in Hz. Table 1 presents the comparative results. From the results, it can be observed that the proposed model outperformed the state of the art. Figure 3 reports the estimation results for the proposed model and benchmark models between 0- and 15-dB SNR. Based on the obtained results, the proposed method achieves higher accuracy on short sequences at 104 samples than the state-of-the-art models.

Table 1: Comparisons in terms of RMSE using SNR=10

Models	SNR	RMSE	Regression	Actual offsite (Hz)	Predicted off-site (Hz)	Frequency error (Hz)
The proposed model	10	**30.45**	**0.9835**	12.31	**13.02**	**17.41**
CNN		37.66	0.87		17.44	22.34
LSTM		39.22	0.832		21.22	26.1
Stacked network		44.21	0.712		34.23	39.32
GRU		37.66	7.34		29.34	20.45

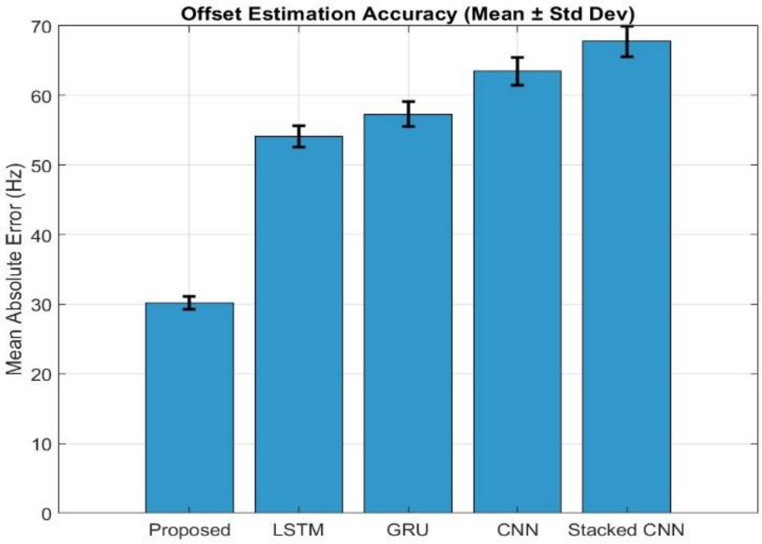


Figure 3: The mean and standard deviation of MAE for different models at 10 dB SNR

Figure 3 shows the Mean Absolute Error (MAE) and its value variance at various models at a 10 dB SNR. The CNN-BiLSTM model has the lowest MAE, which depicts a better performance of the model in terms of the accuracy of the offset's estimation. On the contrary, models such as LSTM, GRU, CNN, and Stacked CNN have a higher value of MAE, and the highest error is recorded in Stacked CNN. The error bars represent the standard deviation, which points to the consistency of the performance of each model. The proposed model is much better than the other ones, as it proves to be robust and reliable in estimating CFO in noisy conditions.

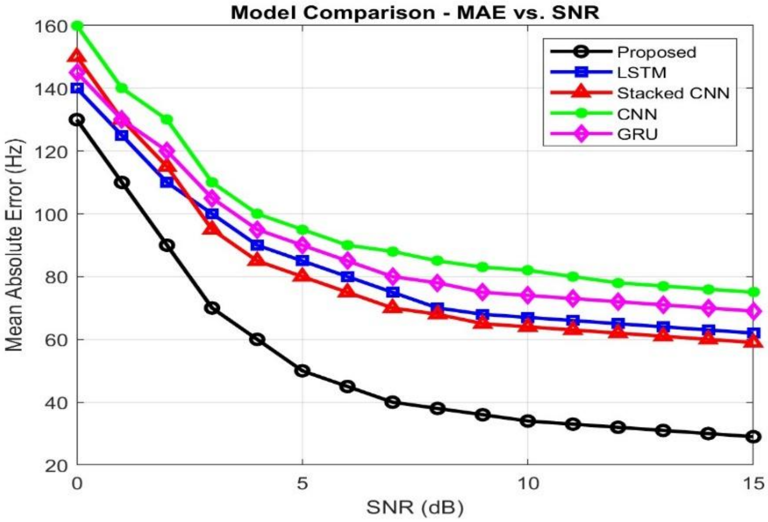


Figure 4: Comparison in terms of MSE with different SNR

Figure 4 presents the comparisons in MAE across SNR levels for the proposed model, LSTM, Stacked CNN, CNN, and GRU. It was noticed that the MAE decreases consistently when the SNR increases for all models, indicating better frequency offset estimation under cleaner signal conditions. However, the proposed model outperforms LSTM, Stacked CNN, CNN, and GRU across the entire SNR range, even when SNR was low, demonstrating superior robustness and generalization. Another observation, when SNR was ranging from 0–5 dB, where noise heavily influences estimation accuracy, the proposed model gained significantly lower MAE than the others. Highlighting its effectiveness in functioning in noisy environments. Stacks LSTM and CNN performed adequately in the mid to high SNR regions, but they performed worse than the proposed model. The CNN and GRU network models performed worse in high-noise environments than all other models. This might mean that they can't fully understand and apply complex time-based properties in these cases.

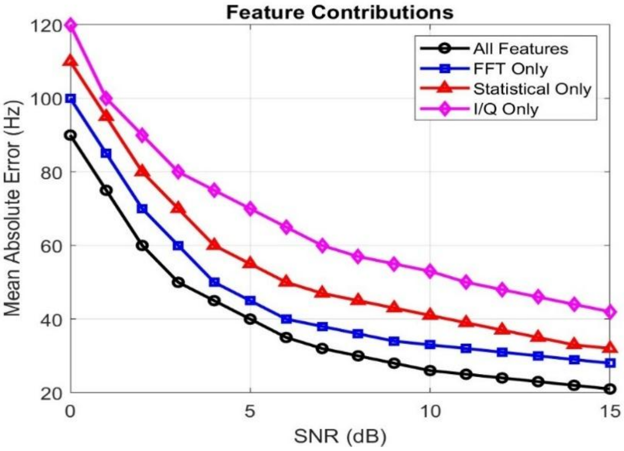


Figure 5: Feature influence on off-site estimation

Figure 5 illustrates the impact of several feature sets on the off-site estimations. The results show that the combination of FFT, statistical, and IQ features always had the lowest MAE. This indicates that using several signal representations together is better. When using only one feature type, for example, FFT features, the model performs relatively well at higher SNRs, demonstrating the frequency-domain features' sensitivity to clean signals. Statistical features also influence moderately, particularly in mid-SNR regions, showing their ability to attain overall signal trends. In contrast, using only I/Q features results in higher estimate error across all SNR levels, indicating that these raw waveform elements alone are sufficient for accurate frequency offset estimation. The results clearly demonstrated the corresponding nature of these feature types, justifying the fusion of all features for improved robustness and accuracy.

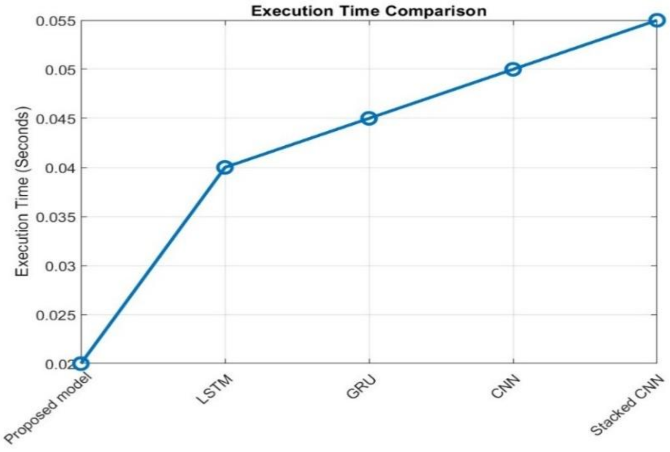


Figure 6: shows the mean computation time in the testing phase

Figure 6 reports the results of execution time for the proposed model, LSTM, Stacked CNN, CNN, and GRU. The proposed model showed the fastest inference time, extensively surpassing LSTM, GRU, CNN, and Stacked CNN. The obtained results proved its suitability for real-time deployment in time-sensitive applications. The proposed model attains a beneficial balance between performance and runtime, making it a great candidate for practical implementations.

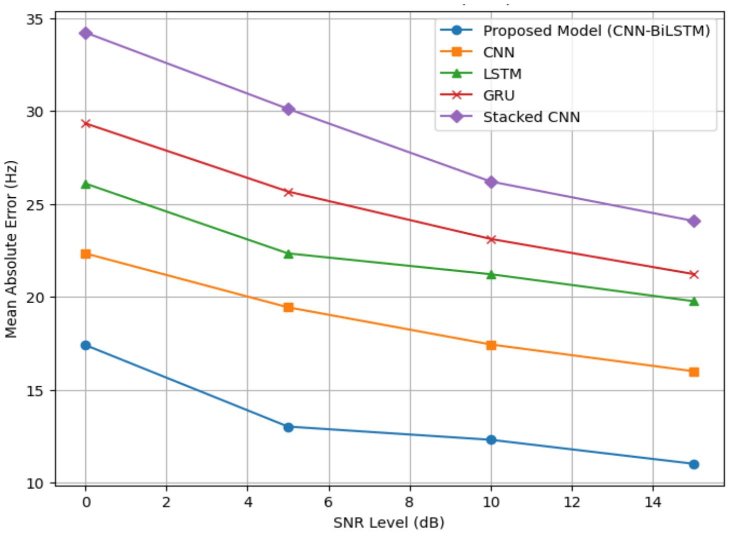


Figure 7: CFO estimation mean absolute error (MAE) vs. SNR levels

In Figure 7, the Mean Absolute Error (MAE) of CFO estimation in the various SNRs of various models is shown, such as the proposed model (CNN-BiLSTM), CNN, LSTM, GRU, and Stacked CNN. The graph indicates that the proposed model has performed the lowest at all SNRs, indicating that the model is more accurate in estimating CFO. The SNR causes the MAE of all models to reduce as the SNR increases, meaning that they perform better in cleaner signal conditions. The given model has been indicated to be more efficient than any of the other models across the SNR range, which is a pointer to its strength and success in CFO estimation even under the noisy conditions.

5 Conclusion

A deep learning-based CFO estimation model based on a CNNBiLSTM network was suggested to predict frequency offsets in noisy conditions, specifically in wireless ad-hoc and sensor networks. The experimental findings indicate that the proposed model is more effective than the traditional and baseline deep learning strategies at all accessible signal-to-noise ratio (SNR) levels. The model demonstrated the lowest Mean Absolute Error (MAE) at 13.02 Hz, significantly outperforming CNN (17.44 Hz) and LSTM (21.22 Hz). Additionally, the Root Mean Square Error (RMSE) for the proposed model was 30.45 Hz, also lower than the CNN (37.66 Hz) and LSTM (39.22 Hz) models, further highlighting its superior performance. Interestingly, the increase in the performance is higher at low SNR levels where the noise has a devastating impact on the synchronization accuracy which indicates the strength and stability of the suggested solution. This enhancement of the CFO estimation is necessary to make sure that there is a reliable and secure communication in sensor-based networks, where synchronization error can largely negatively impact the system performance. The decreasing estimation error in the different SNR conditions also shows that the model is appropriate in the real time use. Future research will concentrate on the verification of the framework to the real-world scenarios of wireless environment, to investigate the scalability of the framework in high mobility and dense network environments, and to integrate adaptive learning mechanisms to monitor changing channel environment over time. Moreover, the hybrid models that combine attention mechanisms or generative adversarial networks (GANs) will be considered to improve the accuracy of the estimations and long-term network performance further.

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