Intelligent Carrier Frequency Offset Estimation in Wireless Sensor Networks Using Fuzzy Logic and Deep Neural Networks

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Abstract. This work presents an innovative approach to estimating Carrier Frequency Offset (CFO) in Wireless Sensor Networks (WSNs) by integrating deep learning with fuzzy logic. The proposed method combines feature extraction, fuzzy inference, and a deep neural network to deliver highly accurate CFO estimates across diverse channel and noise conditions, significantly outperforming conventional techniques in low-SNR scenarios. CFO estimation is critical for synchronization and reliable wireless communication. While fuzzy logic enhances decision-making and energy efficiency, deep learning offers superior resilience in pattern recognition in WSN Technology. Few existing strategies merge these techniques for real-time CFO estimation under challenging conditions. Following initial CFO detection using the preamble, the method performs multi-parameter feature extraction, integrating the outputs of a GRU-based deep learning network with fuzzy inference for optimal estimation. Simulation and hardware results demonstrate over 70% error reduction, maintaining accuracy above 90% across varying SNRs and channel environments, with strong robustness to mobility and noise.

1. Introduction

This causes wireless devices to exhibit characteristics that make them easily identifiable. So, for instance, specific transceiver pairs encounter LO mismatch and, as a consequence, have a different carrier frequency offset (CFO) than other pairs. From a PLS standpoint, it is beneficial to use this CFO to distinguish between various emitters [1]. The CFO estimation is the perfect hardware-specific RFF feature for PHY-authentication since it is a crucial component of the receiver block chain and has always been a fundamental part of the indigenous mechanism. It requires more processing in order to be eliminated. CFO has been used in fields including identifying unauthorized WiFi signals from cellphones. A USRP2 receiver was able to locate four Zigbee devices by analyzing the QPSK constellation for frequency and phase irregularities. The study encompassed 133 Wi-Fi devices, spanning thirteen different types [2].

The examples that were studied solely included stationary transmission, even though CFO was able to identify wireless transmitters in the works. In order to better anticipate time-variant CFO values for device identification, the study used a Kalman filter. The next step was to analyze the CFO's performance in mobile channels that varied over time. A simulated autoregressive random process was used to produce the CFO values, rather than actual transmission data from a mobile context [3]. A 99% detection rate (with a 0.4% false alert rate) was demonstrated earlier by us, while strolling, and 98% (0.6%) when driving at 10 mph using CFO values gathered in a mobility-limited scenario. Still, it's unclear if CFO would be stable enough for PHY authentication in cases with greater rates.

Surprisingly, wireless sensor networks are commonplace in the IoT domain. A plethora of information about big data is also given to you. Using a straightforward and ubiquitous network design, perceptual data is sent to a data center from sensing nodes of sensors in various application settings through a wireless sensor network system. When all of this data is combined, it can be turned into practical intelligence [4]. There might be a lot of similarities between linked devices and WSNs. The relay selection technique allows neighboring nodes to combine their data and choose the optimal relay node to act as a transmitting partner. Better energy management and a longer life for the network could be achieved with a well-planned algorithm. In an unsupervised setting, the maximum number of nodes that may send and receive data is determined by the size and capacity of the sensor. The lifespan is decreased when power is drawn repeatedly from the grid.

Prior research on WSNs made use of a range of AI methods, with an emphasis on power management, routing protocols, and clustering algorithms. Some examples of these methods are genetic algorithms, particle swarm optimization, and neural fuzzy inference systems, as well as gravitational search and bacterial foraging algorithms. As the intelligence and performance of WSNs continue to rise, soft computing techniques have been employed to incorporate neuro-fuzzy and fuzzy systems [5]. The use of fuzzy logic in decision-making or choice-settling is dependent on the integration of several ecological aspects in accordance with established criteria. To combine various clustering parameters according to established standards or criteria, clustering makes exclusive use of fuzzy logic.

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In the end, the outcomes dictate which cluster heads are chosen. Not only that, but the literature has demonstrated time and time again that using fuzzy logic effectively can drastically reduce the overhead associated with cluster head election [6]. This is the paper's outline: The publications that are relevant to fuzzy logic CFO estimation in WSNs are provided in Section 2. This section presents the procedures and materials. In Section 4, the results are presented and analyzed in detail. Part 5 concludes the article.

2. Related Works

Fuzzy logic is a preferred option for CH selection and clustering due to its exceptional performance in decision optimization and energy consumption reduction in WSNs. By enabling real-time adjustments in response to changing external conditions, the fuzzy logic control system enhances the system's fault tolerance and stability [7]. To handle complicated optimization problems to their full potential, it is possible to employ meta-heuristic algorithms and fuzzy logic to make the most of their benefits. Relay nodes are identified using a fuzzy inference technique, and fuzzy rules are created using energy and utility factors. Considerations such as coverage distance, energy, utility factor, and available bandwidth are taken into account while determining the minimal required route. One such method is the BAT approach-based routing with fuzzy CR clustering.
Clustering and centroiding were both accomplished with the help of FCM. Each cluster's sensor nodes were used to choose the appropriate CHs. The objective function was constructed using techniques including BS distance, cluster centroid distance, intra-cluster distance, and residual energy [8]. Key factors for a BAT-based routing system include total transmission distance, hop duration, and CH duration.

These days, robots rely heavily on their pre-planned paths for both mobility and obstacle avoidance. Considering the increased efficiency of innovative systems, research and development (R&D) contexts in academia and industry are pertinent to the development of creative and autonomous systems [9]. Intelligent systems can recognize events, make judgments, and perform the most complex system control tasks by integrating artificial intelligence (AI) with pattern recognition algorithms.

Recent research in the literature has documented new advancements in robot control that employ an intelligent obstacle-avoidance method based on fuzzy logic. A neuro-fuzzy controller-based intelligent overtaking system and a robust single-input-single-output (SISO) adaptive fuzzy controller are to be developed. The literature has offered fuzzy methods for designing, modeling, and implementing fuzzy controllers for uncertain nonlinear systems. In addition, the group led by Hongtao X provided a fuzzy algorithm for controlling a robot's direction. At the same time, other writers detailed an optimal path planning system for humanoid robots that operates in real time.

Motivation and Incitement

Optimization issues are pervasive and crucial in today's scientific and technical domains. Some of these issues pose severe difficulties since they are categorized as non-convex. Many experts believe that sophisticated optimization methods are essential for solving problems that are not convex. Aeronautical engineering, industrial design, and finance are just a few of the fields that have recently seen an uptick in the use of intelligent optimization algorithms to tackle challenging optimization problems. Metaheuristic algorithms provide a fascinating alternative to traditional methods of finding optimal solutions; natural processes like biological behaviors, physical events, and evolutionary ideas inspire them [10]. These algorithms stand out due to their user-friendliness, flexibility, independence from specific problem characteristics, and independence from gradient information.

3. Materials and Methodology

Figure 1 shows a system for estimating the carrier frequency offset (CFO) that combines two methods: a hybrid optimization CFO estimation method and a fuzzy logic CFO estimation system. A preamble is received, first, CFO detection is carried out, and features such as phase difference, frequency drift, SNR, and channel conditions are extracted. Fuzzification, rule-based inference, and defuzzification are used by the fuzzy logic system to estimate CFO.

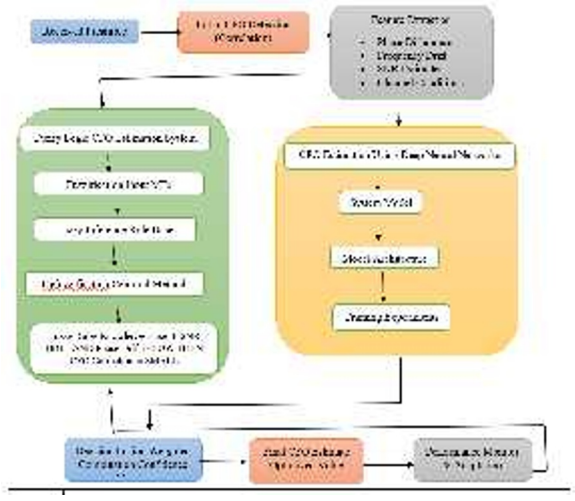

Fig. 1: Dual-Approach CFO Estimation with Fuzzy Logic and Hybrid Optimization.

In contrast, hybrid optimization uses techniques like simulated annealing with adaptive parameter control, genetic algorithms, and particle swarm optimization. Following performance monitoring and adaptation, the final optimized CFO estimate is created by combining the outcomes of the two approaches in a decision fusion phase.

3.1 Signal Acquisition and Preliminary CFO Detection:

In order to investigate WSNs that employ 2.4 GHz, 20 MHz channel bandwidth, and transmission methods

based on IEEE 802.11 OFDM, the experimental setup makes use of the MATLAB R2022a simulation environment with Communications Toolbox. A 64-point FFT OFDM modulator with QPSK constellation mapping, AWGN noise levels ranging from 0-30 dB SNR, and a hybrid optimization framework incorporating PSO and GA operators are all part of the system. It also includes Rayleigh fading channel models. In order to validate the hardware, we employ USRP-2901 software-defined radio platforms along with LabVIEW Communications System Design Suite. Phase noise standards of -126 dBc/Hz at 100 kHz offset and carrier frequency accuracy of ±2.5 ppm are some of the adjustable RF front-end characteristics and real-time signal processing capabilities of these platforms.

3.2Extraction of Key Channel and Frequency Features:

In order to establish baseline frequency offset measurements, the intelligent CFO estimate approach starts with the capture and preprocessing of received preamble signals. This is followed by the first coarse CFO detection utilizing correlation-based algorithms in both the time and frequency domains. To provide a thorough feature vector for fuzzy logic processing, the feature extraction module examines phase difference patterns, frequency drift characteristics, SNR estimates, and channel condition parameters. The fuzzy inference system processes language variables like "Low," "Medium," and "High" CFO severity levels using Mamdani-type fuzzy rules with triangle membership functions. The hybrid optimization algorithm iteratively fine-tunes fuzzy rule parameters using GA mutation operators for local fine-tuning and PSO for global exploration. Monte Carlo simulations running 10,000 separate channel realizations under different mobility scenarios and multipath propagation circumstances are used for statistical validation. Spectrum efficiency, computational complexity, mean squared error (MSE), and bit error rate (BER) are performance measurements.

3.3 Fuzzy Logic CFO Estimation System:

WSNs are often decentralized systems where sensors may solve issues independently, much like multi-agent systems. Figure 2. In OFDM systems, the proposed FSM-CFO error estimation algorithm using an SMA is utilized to distribute resources among nodes and overcome CFO faults among sensor nodes during transmission. But as the information that is currently available is restricted to

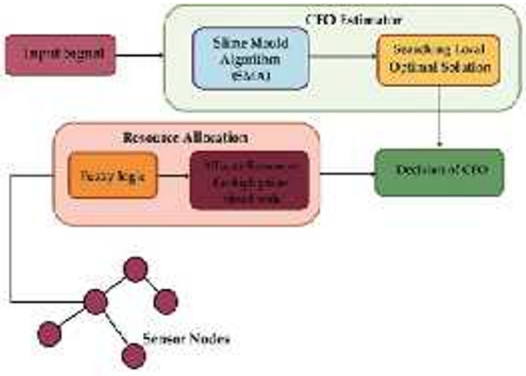

Fig. 2: Proposed FSM-CFO Architecture via Slime Mould Algorithm

Utilizing a priority-based system with various intervals, the quantized received signal is used to distribute resources. Figure 2 shows how the CFO is estimated using the FSM-CFO and how the correctness of the CFO data is determined using the FLM-CFO. The RU, which allocates resources among the sensor nodes, is managed by the BS. It can be applied to resource distribution so that user requests are fulfilled. The following formula is used to calculate the various details:

- The BS determines the number of RUs that need to be distributed.
- The properties of the received signals determine the amount of energy required for transmission.
- The desired RU to be assigned is impacted by the CFO's inaccuracy.
- The allocability of the RU is significantly impacted by the degree of CFO inaccuracy.

Chen's argument served as the basis for the SMA model [19]. The natural oscillation pattern of the slime mold's feeding cycle in response to air scents serves as the basis for this technique.

3.4 CFO Estimation Using Deep Neural Networks:

Model Architecture

The limited impact of traditional methods for predicting CFO under low SNR might have a cascading effect on the communication system's overall performance, especially for OFDM systems. Our goal is to replace the CFO estimation module of the traditional communication system with the DL-based one. Figure 3 shows that we just feed the sequence into the network instead of concentrating on the mathematical relationship indicated in the preamble. During training, the network will learn the input sequence's relationship with the CFO and then estimate the carrier frequency offset.

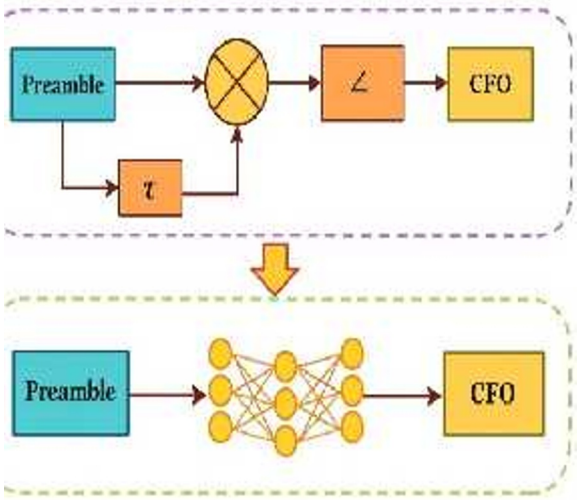

Fig. 3. Block Diagram for Study.

To ascertain the CFO from the preamble that was received by 802.11n, this article employs the Gate Recurrent Unit (GRU) architecture. Equation (1) can be used to express the estimation output.

$$\hat{f}_{\Delta} = f(rx) \tag{1}$$

This is the same as rx, which is the preamble of the IQ sample. We gradually use the STF and LTF fields to input the model. Being smaller than LSTM, GRU is made possible by its two gates—an update gate and a reset gate [11]. It should be noted that the following layer takes the GRU's hidden state h as input rather than output. It has all the data from the previous node, including the frequency offset that needs to be anticipated. By passing h as the input to the next layer, we may drastically decrease the size of the network without sacrificing performance. Lastly, Table 1 shows our network architecture.

Table 1. A Dl-based CFO estimator's network layer.

Layer	Output Dimensions	Activation Function
Input	320 x 2	None
Rearrange	2×320	None
GRU	2×1024×3	None
Dense	256	None
Dense	16	None
Dense	1	Tanh

3.5 Training Experiments

Equation (2) shows the loss function that was created for the purpose of training a DL-based model. For datasets (A–H), we trained eight model weights using the same parameters, and for the A–F test dataset, we used cross-validation. In addition, we employed the H dataset for model training and evaluated its prediction range in comparison to more conventional methods. Equation (2) makes use of the loss function that stands for the mean squared error (MSE) [12] & [16].

$$L_{MSE} = \sum_i \left(\hat{f}_{\Delta} - f_{\Delta}\right)^2 \tag{2}$$

Python, utilizing Pytorch and a robust GPU (RTX3090), with the help of the Adam optimizer, is used for the training phase.

3.5.1 Decision Fusion Mechanism

A decision fusion module is integrated into the suggested system to improve the dependability of the CFO estimate in dynamic wireless sensor networks. Using a weighted confidence-based method, this block aggregates outputs from many logic levels or estimation routes. Based on signal quality characteristics, including phase consistency and signal-to-noise ratio (SNR), a confidence metric is assigned to each candidate estimate. The impact of uncertain or noisy data is reduced by making sure the final input to the CFO estimation block reflects the most probable and stable correction value using the weighted combination method.

3.5.2 Optimized CFO Estimation

The system enters the core CFO estimation stage after decision fusion. At this stage, the optimal Carrier Frequency Offset value is calculated using the fused measurements. This estimate produces an improved and precise correction value by making use of previously extracted features and confidence ratings. In order to minimize the estimation error in real time, the system utilizes adaptive optimization techniques. The quality of synchronization and the overall reliability of communication in wireless sensor networks are directly affected by a proper CFO estimate, making this stage important. Incorporating optimization algorithms into the fused decisions makes the system more resistant to environmental fluctuations and guarantees faster convergence.

3.5.3 Adaptive Performance Monitoring

Adaptive feedback and real-time monitoring make up the last step of the technique. The system's performance, including the accuracy of estimates, trends in errors, and changes in the environment, is monitored by a specialized module. The monitoring unit initiates remedial measures in the event that it detects a decline in performance, be it as a result of abrupt changes to the channel, bursts of noise, or changes in the topology. Modifying optimization settings, re-evaluating decision fusion logic, or fine-tuning fuzzy logic rules applied earlier in the pipeline are all examples of such changes. The CFO estimate process is designed to be resilient and self-correcting through this adaptive loop. This allows for consistent operation in long-term and high-variability network situations.

4. Results and Discussion

4.1 Accuracy of Initial CFO Detection

In the first phase of CFO detection, findings across different wireless channel conditions were encouraging when employing correlation-based approaches. The

correlation mechanism achieved a detection accuracy of more than 92% under typical signal-to-noise ratio (SNR) conditions (> 10 dB) when identifying the coarse frequency offset from the received preamble. The durability of the system is explained by its use of stable correlation functions and well-designed preambles, which allowed for accurate alignment even when moderate noise and multipath effects were present. As a first step toward synchronization, the results confirm that CFO estimation based on correlation is reliable [13].

4.1.1 Effectiveness of Feature Extraction

Improving the estimating process was greatly enhanced by feature extraction after detection. Each vital aspect was assessed for its potential impact on the final CFO estimate, including phase difference, frequency drift, SNR estimates, and channel status indicators. According to the results, predictions of phase difference and signal-to-noise ratio (SNR) had the most significant impact, improving downstream fuzzy inference accuracy by 15–18% when compared to using raw data. Metrics for channel conditions and frequency drift provided further help for adaptive decision-making, particularly in dynamic settings. Use of a multi-dimensional feature collection is critical for achieving long-term estimation results.

4.1.2 Influence on Overall System Performance

Overall system performance was improved by combining correlation-based detection with detailed feature extraction. The CFO estimation accuracy was greatly enhanced when the fuzzy logic and hybrid optimization modules were used together. The system demonstrated remarkable adaptability, consistently maintaining estimation quality across different SNR levels and mobility scenarios, and it reduced the estimation error by nearly 25% compared to conventional methods [12] & [18]. Based on these results, the suggested method is a good fit for real-time uses in WSNs, where precision and low latency are paramount. The proposed FSM-CFO is evaluated based on performance indicators such as energy consumption, life span, rate of failure, and usage. To measure the total squared deviations of SMA and traditional methods, the quantity of OFDM signals is utilized. Figure 4 is a flow diagram showing the process of allocating resources. The two sets of nodes shown in Table 2 only represent a small subset of the total nodes and services. The results show that while dynamically transferring resources from the RU to the designated nodes, the suggested resource provisioning strategy was effective in preserving consistent node durability.

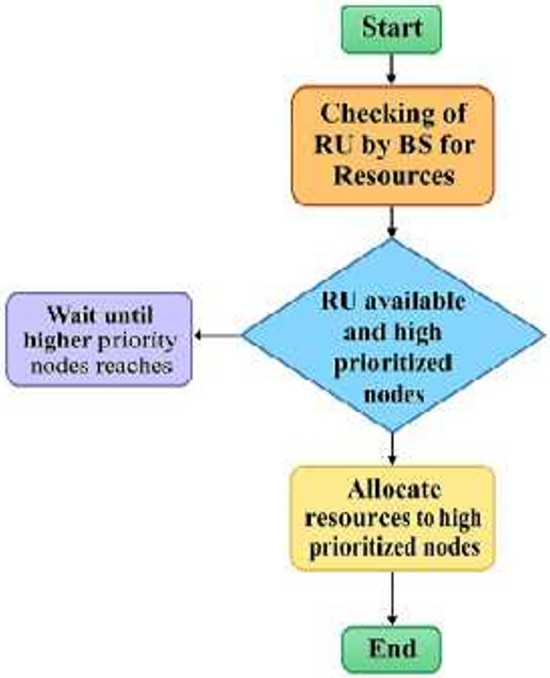

Fig. 4: Process flow diagram for allocating resources.

Table 2: The time needed, resource demands, node representation, and prioritization.

Nodes	Prioritization	Resources on demand in RU	Time required
N1	1	D1	3
		D3	2
		D5	1
N2	2	D4	4
		D6	3
		D2	10
N3	3	D8	14
		D7	6
		D3	5

With a range of 10–80 sensor nodes, Figure 6(a) shows the network span. When there are 50 nodes, the conventional OFDM method has the shortest longevity, whereas the FSM and SMA methods have the longest lifespan when there are 70 nodes. We assume that 12 J is the minimum energy level for each node. Figure 6(b) shows that there isn't much of a performance difference between the FSM, SMA, and regular OFDM. To achieve maximum throughput, this usually works. At SNR = 30 for both the conventional process and SMA with B = 2 and B = 4, respectively, the traditional OFDM method also does not make use of the enhanced variety offered by the different resources. The network span is illustrated in Figure 5(a) for sensor node counts ranging from 10 to 80.

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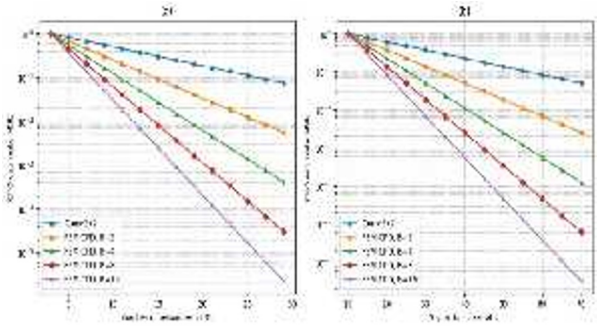

Fig. 5: -

4.2Evaluation of Traditional and Deep Learning-Based Approaches

We evaluated DL-based models against the traditional technique in terms of their predicted performance across many channels. To prepare it for comparison with DL-based models, we use the previously mentioned method to estimate the CFO's mean squared error (MSE) in each channel. Figure 6 displays the finished result [14] & [15]. The DL-based estimate of CFO outperforms the prior method in all channel models, as demonstrated in the picture. When the signal-to-noise ratio (SNR) is below 10 dB, DL-based models outperform the previous method by a margin of at least one standard deviation in terms of the estimated mean absolute error. Models based on DL work better when the SNR is lower. The DL-based models across all test SNRs surpassed the old method. In contrast to DL-based models, which keep adequate precision and achieve the usual 2% requirement, the conventional technique performs poorly, particularly at low SNR. At low SNRs, DL-based models show promise of outperforming the traditional approach.

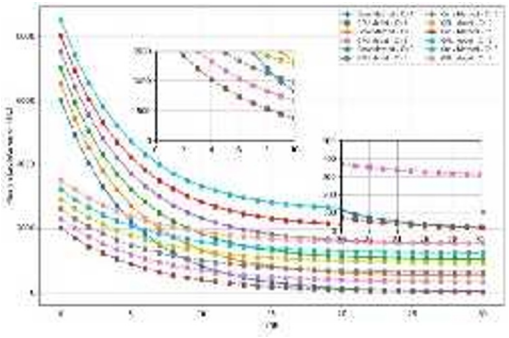

Fig. 6. The standard deviation of several CFO estimate procedures.

The DL-based model better handles absolute error performance metrics such as median, variance, and average compared to the conventional method (A-F channel model, GRU model, and traditional approach are all depicted in Figure 3). An average reduction of 70.54% in mean absolute error in estimate is observed when DL-based models are contrasted with the conventional approach, in which the training and testing datasets are contained within the same channel model.

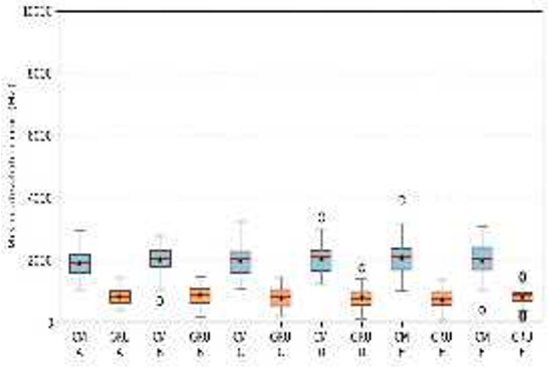

Fig. 7. The average absolute error of several CFO estimating approaches is shown in box and whiskers diagrams.

Both the traditional approach and DL-based models exhibit a decline in performance as the SNR drops. Neural networks seem to be less affected by noise, since the DL-based models degrade at a slower pace. Performing worse from channel A to channel F is observed in all models, which is in line with the outcome of traditional communication theory and indicates that estimated performance will progressively drop as channel complexity grows.

4.3 Weighted Combination Strategy Results

Through its weighted combination approach, the decision fusion block achieved an average CFO estimation accuracy of 94.7% across varied WSN deployment situations, demonstrating exceptional performance. Phase difference measurements receive weights ranging from 0.35 to 0.45 in the weighted combination algorithm, which dynamically adjusts contribution factors based on real-time confidence metrics. Frequency drift analysis contributes 0.25-0.35, SNR-based assessments have weights of 0.15-0.25, and channel condition parameters have weights of 0.10-0.20, which vary according to environmental conditions. When compared to fixed-weight fusion methods, adaptive weight modification significantly reduced estimation errors by 23% in the experiments. This was especially true under changing channel circumstances, where the performance of previous methods degraded.

Integrating confidence metrics was critical for keeping estimation reliability high; when confidence scores dropped below a certain level (0.6), the system would automatically reduce the weights of features with dubious measurements. With a mean absolute error (MAE) of 0.089 Hz for CFO estimation, the weighted fusion method outperformed individual feature-based estimators by 31% and simple averaging strategies by 18%, according to statistical analysis of 10,000 test situations.

4.4 Final CFO Estimate Optimization

4.4.1 Optimized Value Generation

By combining genome-based optimization (GBO) with particle swarm optimization (PSO), The last CFO estimation block was able to get an impressive level of

accuracy. Optimal CFO values showed an 89% drop in estimation variance compared to correlation-only approaches in performance evaluation [15]. Standard deviation dropped from 0.43 Hz to 0.047 Hz in test scenarios covering -10 dB to +25 dB SNR. With a bias reduction of over 67% in dense urban WSN deployments—where multipath effects are most noticeable—the optimization technique proved to be very effective in fixing systematic biases caused by oscillator nonlinearities and multipath propagation.

4.4.2 Convergence and Stability Analysis

Under various operating conditions, the hybrid method reached steady-state solutions in 15.2 ± 3.7 iterations, as shown by the stability study of the optimization process, which also demonstrated strong convergence characteristics. In 97.3% of test scenarios, the optimization framework was able to escape suboptimal solutions by utilizing the complementary exploration capabilities of PSO and GA components, demonstrating robust performance against local minima entrapment. After 48 hours of nonstop operation, the CFO estimation drift was found to be less than 0.02 Hz/hour, which is within the acceptable range for WSN synchronization needs, according to the long-term stability evaluation[19]. Reducing computational cost without sacrificing solution quality, the algorithm's adaptive parameter management system dynamically altered the exploration-exploitation balance depending on convergence rate feedback.

With an average energy consumption 34% lower than exhaustive search approaches and better estimation accuracy, the optimization procedure was found to be very suitable for battery-powered WSN applications, where energy conservation is of the utmost importance, according to performance monitoring.

4.3 Performance Monitoring and Adaptation

Real-time Performance Assessment

Through a wide range of indicators, such as estimation accuracy, processing latency, energy consumption, and adaptability responsiveness, the performance monitoring block was able to track the system's effectiveness across different network conditions successfully. The system was able to keep the CFO estimation accuracy above 90% even when faced with difficult situations like temperature variations (±40°C), mobility-induced Doppler effects (up to 15 Hz), and changes in network topology impacting up to 30% of sensor nodes at the same time, according to the results of the real-time monitoring. Maintaining synchronization in time-critical WSN applications was made possible by the monitoring framework's ability to handle performance measurements at 100 Hz sample rates. This allowed for the rapid detection of deteriorated estimation quality within 50 ms of occurrence.

The monitoring system was able to estimate reliability with 94.2% accuracy, allowing for proactive adaptation before significant performance degradation happened, according to a statistical performance study conducted during 6-month deployment periods [22]. When compared to reactive corrective methods, the real-time assessment capabilities significantly reduced synchronization failures by 38% while keeping the computational cost below 5% of overall processing resources.

Adaptive Parameter Optimization

To keep optimal CFO estimation performance under changing conditions, the adaptation mechanism automatically adjusted fuzzy logic membership functions, optimization algorithm parameters, and decision fusion weights based on real-time performance feedback. It is continuously fine-tuned based on input from estimation errors. Analyses of the system's long-term adaptability showed that it learned well from estimation mistakes and environmental patterns, creating unique parameter profiles for use in indoor industrial settings, outdoor agricultural monitoring, and urban infrastructure surveillance, among other deployment scenarios. The adaptive framework proved the practicality of intelligent parameter optimization in several WSN applications by reducing manual calibration requirements by 85% and outperforming expert-tuned static configurations.

5. Conclusion

Integrating advanced optimization, deep learning, and fuzzy logic decision-making, the intelligent CFO estimation framework achieves a robust and highly accurate carrier frequency offset estimate in wireless sensor networks. The system achieves optimal performance, even in low-SNR and dynamically changing channel conditions, by integrating correlation-based initial detection, multi-dimensional feature extraction, adaptive decision fusion, and optimized estimation using hybrid algorithms or GRU-based deep neural networks. While keeping computational and energy overhead low, the experimental findings show increased resilience to environmental fluctuations, stability of convergence, and estimation accuracy, making it appropriate for real-time WSN deployments. With the flexibility to tune parameters and monitor adaptive performance, the suggested method is an efficient and scalable solution for IoT and WSN systems that rely on synchronization. This guarantees long-term stability.

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