Advanced hybrid algorithms for precise multipath channel estimation in next-generation wireless networks

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Article Info

ABSTRACT

Multipath channels continue to present challenges in wireless communication for both 5G and 6G networks. A multipath channel is a phenomenon in wireless communications where signals traverse from the sender to the receiver along various paths. This end occurs due to the reflection, diffraction, and refraction of signals of various objects and structures in the environment. Such pathways can cause symbol interference in the transmitted signal, leading to communication issues. To this end, our paper proposes the integration of three algorithms: teaching-learning-based optimization (TLBO), particle swarm optimization (PSO), and artificial neural networks (ANN). This combination effectively analyzes and stabilizes the transmission channel, minimizing symbol interference. We have developed, simulated, and evaluated this hybrid approach for multipath fading channels. We apply it to various coding schemes, including tail-biting convolutional code, turbo codes, low-density parity-check, and polar code. Additionally, we have explored various decoding methods such as Viterbi, maximum logarithmic maximum a posteriori, minimum sum, and cyclic redundancy check soft cancellation list. Our study encompasses new channel equalization schemes and coding gains derived from simulations and mathematical analysis. Our proposed method significantly enhances channel equalization, reducing interference and improving error correction in wireless communication systems.

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1. INTRODUCTION

As we delve into the ever-evolving landscape of wireless communication networks, pursuing higher data rates, enhanced reliability, and the ability to support an increasing number of services has led us beyond the realms of 5G and 6G networks [1]. This relentless march toward more advanced communication technologies has unearthed numerous opportunities and challenges, and one of the core challenges lies in dealing with multipath channels. Multipath channels are a ubiquitous feature of wireless communication, arising from the complex interplay of signals as they bounce off, diffract, and refract through various environmental obstacles and structures. The consequence of this phenomenon is the existence of multiple signal paths, each taking a distinct route from the transmitter to the receiver. This multipath propagation engenders interference between the symbols in the transmitted signal, leading to a phenomenon known as inter-symbol interference (ISI). ISI poses a significant obstacle to achieving high data transmission rates, especially in scenarios where signals are

subject to severe multipath propagation, such as in urban or indoor environments. Navigating the intricacies of multipath channels and mitigating the challenges posed by ISI require innovative solutions that extend beyond the capabilities of 5G and 6G networks.

Researchers and technology suppliers have been motivated to discover innovative methods to tackle these challenges, as they substantially impact wireless communication quality and the radio spectrum's effective utilization. The related works of researchers, including Sattiraju *et al.* [2], examined the performance of deep learning (DL) architectures compared to the existing least-square (LS) channel estimation used in C-V2X. The results of these studies show that the suggested DL architecture works better than the old C-V2X channel estimation methods, especially when mobile speeds are high. Other researchers, including Mohammed *et al.* [3], conducted studies evaluating the effectiveness of deep learning-based channel estimation (CE) in comparison to conventional techniques such as least-square (LS) and minimal mean-square error (MMSE) estimators. Vidhya and Kumar [4] proposed a hybrid methodology that integrates particle swarm optimization (PSO) and genetic algorithms (GA) to address the challenge of channel estimation in multiple-input, multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) systems. Kadhim and Sallomi [5] proposed methodology utilizes the sparsity of RIS channels to reduce the training complexity of the CNN model. Additionally, the study employs PSO to optimize the hyperparameters of the CNN model. The simulation results indicate that the suggested method achieves accurate channel estimation at a significantly reduced computational cost compared to earlier methods.

Nahar *et al.* [6] introduced a new method for channel estimation (CE) in multi-carrier wireless communication systems, specifically in orthogonal frequency division multiplexing (OFDM) systems and code division multiple access (CDMA). The proposed approach combines the local search (LS) technique with the particle swarm optimization algorithm. The simulation showed that the proposed CE of the MIMO-OFDM system can significantly result in better BER performance compared with other techniques. Arora and Chawla [7] combined two optimization techniques, the PSO and moth flame optimization (MFO) method, used to optimize the performance rate in the same field. Sohail *et al.* [8] researched the precise and prompt collection of extensive channel state information (CSI). They addressed an optimization challenge that can be tackled using heuristic optimization methods such as genetic algorithms, particle swarm optimization, and differential evolution.

Rahhal [9] utilized the PSO algorithm to identify the most optimal cluster members in a wireless sensor network (WSN) based on a fitness function generated from the channel condition. This method demonstrates the ability to rapidly and expeditiously achieve optimal cluster formation. Gondela *et al.* [10] proposed a method for multiuser detection (MUD) in direct sequence-code division multiple access (DS-CDMA) systems operating over generalized-K (GK) fading channels. The strategy utilizes the teaching-learning-based optimization algorithm (TLBO) with a two-stage initialization (TSI) approach. This approach demonstrates notable improvements in performance as the signal-to-noise ratio (SNR) and diversity order grow, particularly in the presence of heavy-tailed impulsive noise. Ouali *et al.* [11] introduced a filter that consists of two layers: a type2-fuzzy autoregressive filter and the training of membership function parameters. This filter operates as a feedback mechanism. The second layer employs a teaching learning-based optimization algorithm to adjust the settings of the type2-fuzzy adaptive filter. This adjustment aims to minimize the criterion function and achieve signal reconstruction. The method surpasses denoising in terms of noise power levels and standards views.

In this paper, we introduce an advanced hybrid algorithm that synergizes the capabilities of teaching-learning-based optimization (TLBO), particle swarm optimization (PSO), and artificial neural networks (ANN) for the precise estimation of multipath fading channel characteristics in wireless communication systems. This novel methodology aims to optimize the parameter estimation of channel filters, significantly enhancing the equalization process and effectively mitigating symbol interference in data transmission. Our method uses the strong optimization abilities of TLBO and PSO to fine-tune the weights and biases of ANNs. This proposition makes finding and fixing problems in wireless transmission signals easier. We rigorously evaluate the efficacy of this hybrid algorithm using diverse datasets featuring signals encoded with various error-correcting codes, such as turbo codes, low-density parity checks (LDPC), and polar encoders. These tests are conducted under various channel conditions to ensure a comprehensive analysis.

The empirical results demonstrate that our method performs better than several contemporary techniques, particularly precision and operational efficiency. This result is significant for new 5G and 6G networks. Our study shows that hybrid optimization strategies can help a lot with the complex problems of interference and symbol distortion in wireless signal transmission. This innovative approach opens new avenues for enhancing communication reliability and quality in advanced telecommunication systems. The subsequent sections of the paper are organized in the following manner: section 2 introduces sophisticated channel-coding methods. Section 3 outlines the research methodology employed in this study. Section 4 shows the simulation and results, comparing various situations. Finally, section 5 provides the conclusion.

2. ADVANCED CHANNEL CODING SCHEMES

Advanced channel coding is a pivotal strategy for ensuring reliable and efficient data transmission across the air interface in 5G and 6G networks. This technique plays a crucial role in mitigating the impact of noise, interference, and other forms of impairment that may compromise the integrity of transmitted data. By integrating redundant information into the data stream, channel coding significantly reduces the likelihood of data corruption. Implementing sophisticated channel coding methodologies is indispensable to augment the air interface performance in 5G and 6G networks. Notably, high-tech error-correction codes like Polar codes and low-density parity-check (LDPC) codes have shown to be very useful in modern communication systems. These coding strategies facilitate the high-speed, low-latency connectivity essential for supporting emerging applications and use cases within 5G and 6G network environments. Enhancing data transfer reliability and efficiency through these methods is critical in advancing next-generation network technologies.

2.1. TBCC codes

In this study, we investigate using a specific error-correcting code within digital communication systems: the tail-biting convolutional code (TBCC). TBCC is a subset of convolutional codes, which are pivotal in adding redundancy to transmitted data by encoding the information into a sequence of symbols [12]. Decoding these codes can be executed through several methods, with the Viterbi algorithm being a prominent one. A trellis diagram is used in this algorithm to figure out the path metric value, which makes decoding convolutional codes easier.

Adiono *et al.* [13] proposed a VLSI architecture for the reversed-trellis TBCC (RT-TBCC) method, highlighting further advancements in this field. This innovative approach revises the traditional direct-terminating maximum-likelihood decoding procedure to enhance the correction rate. The proposed architecture is more computationally efficient and resource-effective than existing direct-terminating maximum likelihood (ML) decoders. This architecture is evaluated through simulations, system-on-chip implementations, and field programmable gate array (FPGA) synthesis. The focal point of this research is a comparison of convolutional codes, specifically the TBCC, with a memory order of $m = 16$, which adheres to the LTE standards.

2.2. Turbo codes

In 1993, Claude Berrou and his colleagues introduced turbo codes, a revolutionary class of error correction codes. These codes are notable for their capability to approach Shannon's theoretical channel capacity limit with an unprecedented proximity of just 0.5 decibels (dB). This groundbreaking development in information theory marked a significant step forward in achieving efficient data transmission with minimal error rates. Turbo codes employ a dual structure of convolutional encoders, which is pivotal in forming these codes. The decoding process of turbo codes is accomplished iteratively, utilizing the maximum a posteriori probability (MAP) algorithm. These codes stand out for their recursive nature, allowing prior outputs and the current input sequence to influence the output. This recursive output mechanism enhances the robustness and efficiency of the codes, particularly in scenarios involving longer block lengths.

The exceptional performance of turbo codes has led to their widespread adoption in various communication sectors. Their application ranges from deep space exploration missions, where reliable long-distance communication is paramount, to terrestrial mobile communications, including 3G and 4G networks. Turbo codes' high efficiency and low error rates make them an indispensable tool in these areas [14]. Recent research has focused on developing and implementing turbo-coding in 5G technology. A notable project involved designing and configuring a Turbo coder tailored explicitly for 5G networks [15]. This project utilized advanced hardware description and verification tools such as Tanner, Verilog HDL (Xilinx), and ModelSim for the individual configuration of the encoder and decoder. Implementing turbo coding is pivotal in developing 5G technology, which demands high-speed, low-latency communication with minimal error rates. The researchers' success in significantly enhancing data transmission reliability plays a crucial role in the evolution of 5G networks, promising to revolutionize how we communicate and access information.

2.3. LDPC code

LDPC codes, introduced in the 1960s [16], represent a class of linear error-correcting codes characterized by low encoding and decoding complexity. These codes are fundamentally based on sparse matrices, allowing for efficient error correction in various communication channels, including wireless and optical networks. The efficiency of LDPC codes has been instrumental in their integration into the 5G network infrastructure. Notably, the 5G LDPC code, categorized as a quasi-cyclic LDPC (QC-LDPC) code, is defined by two base graphs and is anticipated to play a significant role in the technological framework of 6G networks [17].

Another variant, the rate-compatible raptor-like quasi-cyclic low-density parity-check (RL-QC-LDPC) codes, offers remarkable performance and flexibility. Due to their enhanced error correction capabilities, these codes have been widely accepted in 5G new radio (5G-NR) technical specifications [18]. The research by Zenkouar *et al.* [19] used the Group Shuffled Belief Propagation (GSBP) method to make the GF(q) LDPC encoder and decoder work on an FPGA. These non-binary LDPC codes work exceptionally well with short block lengths and have error correction rates close to the Shannon limit over GF (16). They were modeled using VHSIC hardware description language and ModelSim 6.5.

The study of Ouakili *et al.* [20] introduced a new LDPC decoding algorithm combining normalized min-sum and modified-weighted bit-flipping (NMSMWBF), exhibiting superior performance over traditional NMS by 0.25 dB in bit error rate (BER) over AWGN channels. Razi *et al.* [21] also came up with two better hard-decision algorithms: Adaptive gradient descent bit-flipping (AGDBF) and adaptive reliability ratio weighted GDBF (ARRWGDBF). When implemented in real-time on digital signal processors, these work better than soft-decision algorithms, achieving faster convergence and less processing time and memory usage. For comparative purposes, this work examined an LDPC code based on 5G requirements [22]. The decoding process employs the Min-Sum algorithm, highlighting its efficiency in terms of error correction within the 5G network framework.

2.4. Polar codes

Polar codes, introduced by Arikan [23], represent a class of linear block codes that utilize a unique coding scheme. This scheme involves transforming a set of independent and identically distributed (iid) bit channels into channels with varying error rates, leveraging their polarizing properties. Due to their high-performance capabilities, these codes are increasingly recognized as promising candidates for data transmission in emerging 6G networks [24], [25].

The systematic turbo-polar code (STPC) with an early termination (ET) mechanism that Hamad *et al.* [26] proposed is a notable development in the field of polar codes. This mechanism employs an ideal scaling factor (SF) estimation technique, which has been shown to enhance the BER performance of STPC. The SF estimation leads to a 1 dB improvement in BER over the traditional systematic polar code and a 0.3 dB improvement with a 64-bit code. The novel strategy involves using the estimated SF value at the second component decoder and the decoded frozen bits as a criterion for stopping each decoding iteration. This approach reduces the average number of iterations by half without increasing the system's complexity and achieves BER results comparable to codes with a fixed number of iterations. The cyclic redundancy check successive cancellation list (CRC-SCL) decoding method for Polar codes [27]–[29] was used for comparisons of the CRC-SCL method, with a list size of $L = 16$ and a 16-bit CRC.

3.   SYSTEM MODEL

Suggesting a hybrid method that integrates TLBO, PSO, and ANN to estimate the parameters of channel filters. This approach aims to enhance equalization and minimize inter-symbol interference in multipath fading channels. This technique seeks to exploit the advantages of each method: TLBO for producing a robust initial estimate, PSO for optimizing the solution using a simulated social behavior model, and ANN for refining the parameters with its adaptive learning capabilities. Our model consists of multiple components, each playing a distinct role in addressing the challenges posed by multipath fading channels, thereby improving the system's overall performance.

3.1. Multipath fading channel model

The multipath fading channel can be modeled as:

$$y(t) = \sum_{i=1}^{N} h_i . x(t - \tau_i) + n(t) \tag{1}$$

where $y(t)$ is the received signal, $x(t)$ is the transmitted signal, h_i are the channel coefficients for the i^{-th} path, $n(t)$ is the noise in the channel, and N is the number of paths.

3.2. ANN model for parameter estimation

The ANN is used to estimate the channel parameters like:

$$h(t) = \sum_{i=1}^{N} a_i \, \delta(t - \tau_i) \tag{2}$$

Based on the received signal:

$$y(t) = \big(x(t) * h(t)\big) + n(t) \tag{3}$$

The ANN might be structured as follows:
- Input layer: Takes in features derived from $y(t)$. These features could be various statistical properties or transformations of the received signal, such as its power spectral density, autocorrelation, or any other feature that captures the essence of the fading channel. Let's denote the input features as a vector $x \in R^n$ and n is the number of input features.
- Hidden layers: Multiple layers, each with a nonlinear activation function (like rectified linear unit (ReLU) or sigmoid) denoted by σ, is then applied:

$$a^{(l)} = \sigma(Z^{(l)}) \tag{4}$$

Consider a network with L hidden layers. Each layer l applies a linear transformation followed by a nonlinear activation function to its input. The linear transformation in layer l can be represented as:

$$z^{(l)} = W^{(l)}a^{(l-1)} + b^{(l)} \tag{5}$$

where $W^{(l)}$ and $b^{(l)}$ are the weights and biases of layer l and $a^{(l-1)}$ is the output from the previous layer (or the input x for $l = 1$).
- Output layer: Provides estimates of the channel parameters.

3.3. PSO-TLBO hybrid optimization

The TLBO-PSO hybrid algorithm optimizes the weights and biases of the ANN. This process can be abstracted as:
a. Initialize a population of candidate solutions (both teachers in TLBO and particles in PSO).
b. Evaluate the fitness of each candidate (how well the ANN with those weights or biases estimates the channel parameters).
c. Apply TLBO and PSO operators to update candidates:
    - TLBO: Based on the teaching phase and learning phase.
    - PSO: Update the velocity and position of particles based on personal and global best positions.
d. Iterate until a stopping criterion is met (like a maximum number of iterations or a desired error threshold).

3.4. Equalization model

Once the channel parameters are estimated, they can be used in an equalization algorithm to mitigate the effects of multipath fading. A new, widely linear equalizer has been proposed by Petitpied *et al.* [30]. A common approach is using a linear or decision feedback equalizer. For example, a linear equalizer could be modeled as (6):

$$\hat{x}(t) = \sum_{j=1}^{M} w_j \cdot y(t - j) \tag{6}$$

where $\hat{x}(t)$ is the estimated transmitted signal, w_j are the equalizer coefficients, and M is the number of coefficients in the equalizer.

The hybrid PSO-TLBO-ANN pseudo-code has been applied in the manner shown as follows:

```
Input: Channel characteristics, SNR, Population size, Max Iterations, ANN architecture
Output: Optimized ANN weights, Performance metric
(*Initialization*)
Initialize the ANN with a given architecture and random weights
Initialize the population of particles (weights) and their velocities
Define PSO parameters: cognitive coefficient (c1), social coefficient (c2), and inertia
weight (w)
(*Optimization Loop*)
While (generation count < Max Iterations) do:
    (*PSO Phase*)
    For each particle do:
        Calculate the particle's fitness using the ANN and channel model
        Update the particle's personal best if the current fitness is better
        Update the global best if the current fitness is better than the global best
    End For
    For each particle do:
        Update the particle's velocity based on its personal best, global best, and current
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     velocity
        Update the particle's position based on the new velocity
        Apply the new weights to the ANN
        Calculate the new fitness using the ANN and channel model
        Update the personal and global bests if the new fitness is better
     End For
      (*Teacher Phase (TLBO)*)
     For each particle (as a learner) do:
        If (particle's performance is better than the mean performance of the population)
then:
           Update the particle's position towards the best solution (teacher)
        EndIf
     End For
     (*Learner Phase (TLBO)*)
     For each particle do:
        Select another particle randomly
        If (selected particle's performance is better) then:
           Move the particle towards the selected particle
        Else
           Move the particle away from the selected particle
        EndIf
     End For
     (*ANN Training Phase*)
     Train the ANN using the best weights found by the hybrid PSO-TLBO
     Evaluate the ANN's performance on a validation set
     (*Update PSO parameters based on feedback*)
     Adjust the PSO parameters (c1, c2, w) if necessary, based on the performance
     (*Increment the generation count*)
     generation count = generation count + 1
End While
(*Output the best solution*)
Return the best set of weights and the corresponding performance metric
```

The transmission chain in a multipath channel is described in several steps, as follows:

The transmission mechanism in the multipath channel depicted in Figure 1 can be decomposed into numerous sequential steps:
− Data source: This is the starting point where the data to be transmitted is generated.
− Channel encoding: Techniques like LDPC or Polar coding encode the data for error correction capabilities.
− Modulator: The encoded data is then modulated using a scheme such as quadrature phase shift keying (QPSK) or quadrature amplitude modulation (QAM) to prepare it for transmission over the channel.
− Multipath channel: The modulated signal travels through a channel with multiple paths due to reflections and scattering, which is typical in wireless communication environments.
− Channel estimation: Techniques PSO-TLBO-ANN are used to estimate the channel characteristics, which is critical for the correct data reception.
− QPSK demodulator: The signal is then demodulated from the QPSK scheme back to a form that can be decoded.
− Channel decoding: The demodulated data goes through channel decoding using techniques like Viterbi, max-log-MAP, min-sum, SC, or CRC-SCL to correct any errors from the transmission process.
− Equalization: This stage makes up for the interference and signal distortion that the multipath channel causes.
− Data sink: The data is received and processed at the destination.

The block diagram in Figure 2 involves a sophisticated hybrid algorithm combining particle swarm optimization, teaching-learning-based optimization, and artificial neural networks to enhance the performance of filters in addressing multipath fading channel issues in wireless transmission. The description of this process is as follows:

a. Initialization

The process begins by generating an initial population of particles, each representing a potential solution, and placing them randomly within the solution space. Initial settings of the algorithm are defined, including the size of the population, the number of iterations, and parameters specific to the PSO, TLBO methods, and the ANN configuration.

b. Performance assessment using TLBO

Each particle's performance is then evaluated. This end uses the TLBO method, which enhances the particle's position in the solution space based on a teaching-learning paradigm. Concurrently, the ANN method predicts potential damage locations in the wireless transmission signal.

c. Selection of the best particles

Based on their assessed performances, the best-performing particles are selected for participation in the subsequent iteration.

d. Position update using PSO and performance reassessment

The chosen particles then undergo a position update using the PSO technique. This step optimizes their placement in the solution space, aiming for a better approximation. After updating their positions, their performances are reassessed using the TLBO and ANN methods. This reassessment focuses again on predicting potential damage locations in the signal.

e. Iterative optimization

These steps are iteratively repeated for a predetermined number of iterations. The algorithm refines the solutions during each iteration, gradually converging towards an optimal state.

f. Final outcome

Upon reaching the optimal state, the algorithm yields the most favorable positions for identifying damage in the wireless transmission signal. It also provides insights into its overall performance, mainly focusing on the speed and accuracy with which it can identify damages caused by the noisy channel.
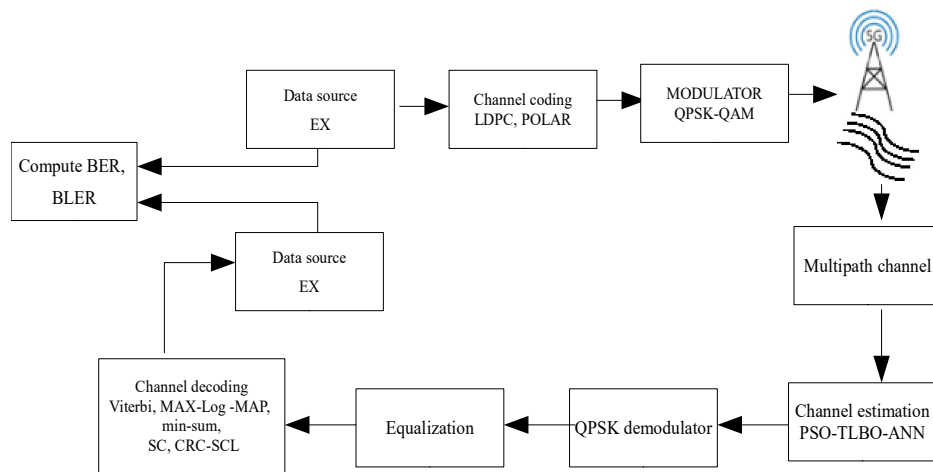
Figure 1. Transmission chain in a multipath channel
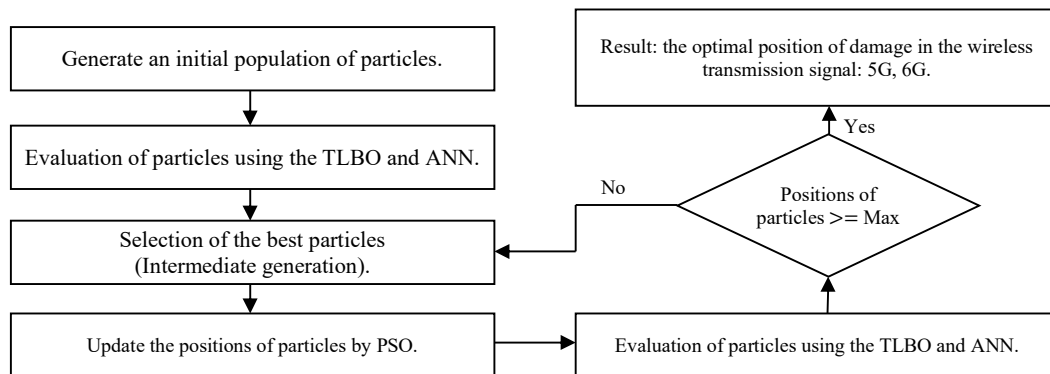
Figure 2. Block diagram of PSO-TLBO-ANN proposed

The hybrid PSO-TLBO-ANN method synergistically integrates the key strengths of each approach PSO's efficient optimization capability, TLBO's learning-based enhancement, and ANN's accurate prediction ability to enhance the reliability and efficacy of signal transmission in a noisy, multipath fading channel. Incorporating particle swarm optimization facilitates a flexible and responsive optimization procedure, enhancing the system's ability to traverse intricate solution domains efficiently. Additionally, the integration

of TLBO strengthens the learning component, guaranteeing continual improvement of the system over time and utilizing ANN to aid in generating exact predictions, which is crucial for dependable signal processing in demanding conditions. These combined qualities make the hybrid technique particularly suited for handling the subtleties of multipath fading channels, where traditional methods might fall short.

4.   RESULTS AND DISCUSSION

This study evaluates the Polar, Turbo, LDPC, and TBCC codes using multipath fading and additive white Gaussian noise (AWGN) channels, together with the eight-phase shift keying (8PSK) modulation scheme, as described in Section 2. This evaluation aims to determine each coding scheme's efficacy in preserving signal integrity in difficult channel conditions. Table 1 presents a comprehensive list of the parameters utilized, offering a clear overview of the experimental configuration and facilitating a thorough comparison of the various coding schemes. The evaluation findings will provide valuable insights into communication scenarios' most effective coding approach, particularly problems such as AWGN and multipath fading.

Table 1. Simulation parameters

Parameters	Specifications			
Channel	AWGN + Multipath			
Modulation	8PSK,			
Information block length (bits)	1024 bits			
Code rate	2/3			
Coding schemes	TBCC	Turbo	LDPC	POLAR
Decoding algorithm	Viterbi	Max-log-MAP (20 iteration)	min-sum (50 iterations)	CRC-SCL 16
Channel estimation	PSO-TLBO-ANN			
Channel equalizer	ANN-TLBO-PSO			

The results of our comprehensive simulation study are meticulously presented in Figures 3 through Figure 8, illustrating the bit error rate (BER) as a function of the signal to noise ratio (SNR). This study demonstrates a significant enhancement in the performance of various coding methods, notably polar, turbo, low-density parity-check (LDPC), and tail-biting convolutional codes (TBCC) when they are integrated with a sophisticated hybrid algorithm combining particle swarm optimization, teaching-learning-based optimization, and artificial neural networks. This hybrid approach, specifically designed to estimate multipath channel effects, showcases an exceptional improvement in coding efficiency, surpassing other traditional coding methods by approximately 0.5 decibels (dB), as detailed in Figure 4 to Figure 8.

In particular, Figure 3 highlights the superior efficacy of polar codes when combined with cyclic redundancy check successive cancellation list (CRC-SCL) decoders for a block length of K=1024 bits. This setup outperforms almost all other coding schemes, achieving gains of 0.3 dB over turbo codes, 0.4 dB over LDPC codes, and a remarkable 0.7 dB over TBCC. The graph also reveals that turbo codes have a slight edge over TBCC, and they marginally surpass LDPC codes by about 0.1 dB.

Figure 4 through Figure 8 focus on the innovative hybrid PSO-TLBO-ANN algorithms employed to predict the behavior of additive white gaussian noise (AWGN) channels affected by multipath fading. These algorithms were tested using signals encoded with error-correcting codes, including TBCC, Turbo codes, LDPC, and Polar encoders. According to Figure 4, when applied to polar codes, the hybrid algorithm demonstrates superior performance over the turbo, LDPC, and TBCC codes, with gains of 0.3 dB, 0.4 dB, and 0.8 dB, respectively. The simulations reveal a marginal yet noteworthy improvement in the performance of turbo codes compared to LDPC codes, with a gain of 0.7 dB over TBCC. The enhanced performance can be attributed to the TLBO and PSO strategies, which optimize the positioning of particles within the solution space, coupled with using ANNs to accurately predict potential signal impairments, such as damages or distortions, in wireless transmissions. Our findings suggest that employing robust encoding methods like Polar, TLBC, and Turbo codes can be highly effective for 5G and 6G communication technologies, particularly in mitigating issues related to noisy channels.

The hybrid PSO-TLBO-ANN algorithm, as evidenced by our simulations, demonstrates superior capability in detecting and compensating for various transmission impairments, including intersymbol interference, typically induced by noisy communication channels. This advancement marks a significant step forward in enhancing the reliability and efficiency of next-generation wireless communication systems.
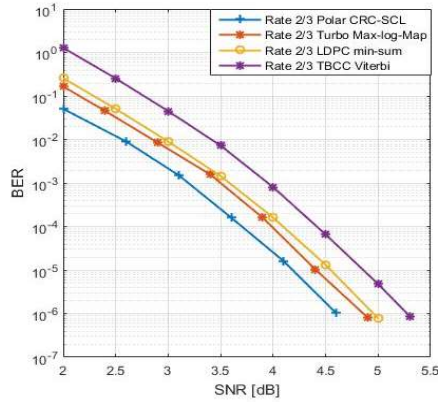
Figure 3. Comparison of Polar codes, Turbo codes, LDPC, and TBCC in multipath fading channels at a rate of 2/3
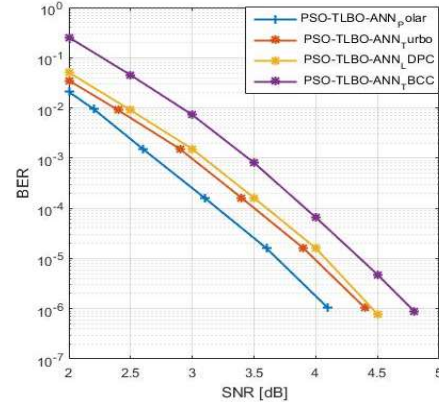

Figure 4. Comparison of error-correcting codes using hybrid PSO-TLBO-ANN estimation in multipath fading environments
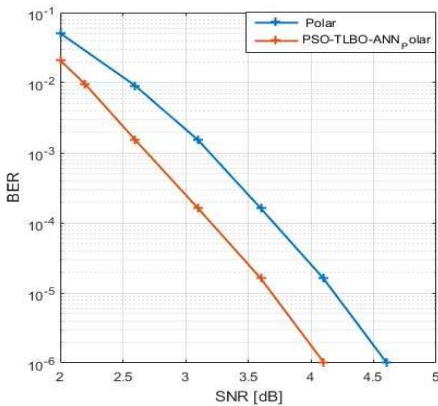

Figure 5. Comparison of Polar codes and Polar codes with hybrid PSO-TLBO-ANN estimation in multipath fading environments
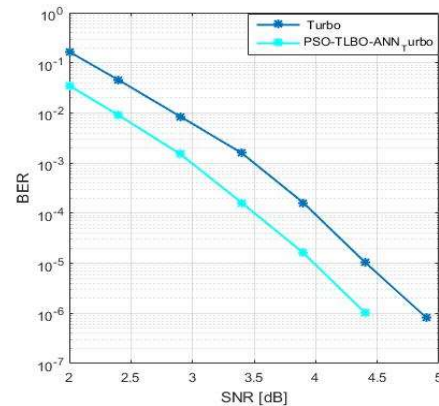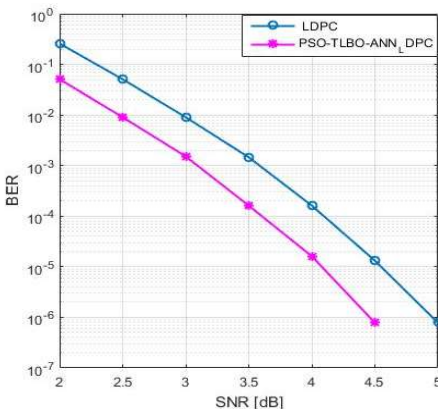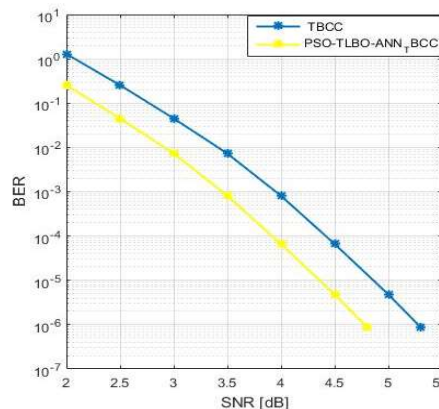

Figure 6. Comparison of Turbo codes and Turbo codes with hybrid PSO-TLBO-ANN estimation in multipath fading environments

Figure 7. Comparison of LDPC codes and LDPC codes with hybrid PSO-TLBO-ANN estimation in multipath fading environments

Figure 8. Comparison of TBCC codes and TBCC codes with hybrid PSO-TLBO-ANN estimation in multipath fading environments

5.   CONCLUSION

This study presents the outcomes of a novel hybrid methodology that synergistically integrates the strengths of teaching-learning-based optimization, particle swarm optimization, and artificial neural network techniques. This innovative hybrid approach adeptly compensates for the limitations of each method by leveraging their collective advantages. ANNs excel in discerning complex patterns and delivering precise predictions. In contrast, TLBO and PSO are renowned for their efficiency in swiftly identifying optimal solutions within a given solution space. This amalgamation enhances the accuracy in detecting transmission signal impairments. The algorithm's adaptability is further demonstrated by its successful application to signals encoded with various error-correcting codes, including TBCC, turbo codes, LDPC codes, and Polar encoders. This versatility suggests that the algorithm is not confined to a single signal type. In practical terms, the hybrid PSO-TLBO-ANN approach significantly boosts the performance of Polar, Turbo, LDPC, and TBCC codes in multipath channel estimations. It surpasses other coding techniques by approximately 0.5 dB. More specifically, the hybrid model yields a performance enhancement of 0.3 dB for Polar codes, 0.4 dB for LDPC codes, and 0.8 dB for TBCC compared to the Turbo codes. Conclusively, this research paves the way for more reliable and precise communication in 5G and 6G wireless networks. The proposed algorithm effectively mitigates the detrimental effects of noisy channels, marking a significant stride in advancing wireless communication technologies.

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