

Channel Estimation in Differential Chaos Shift Keying-based Multiple-Input Multiple-Output Space-time Block Coding Communication Systems Using Deep Learning

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Abstract—Multiple-Input Multiple-Output (MIMO) systems are fundamental to modern mobile communications, enabling beam steering, enhanced data capacity, and diversity gains in 5G networks. Space-Time Block Coding (STBC) improves the data rate of MIMO by creating orthogonal channels, yet this typically requires Channel State Information (CSI) obtained through pilot-based training. However, no existing algorithm can estimate the channel matrix for a general STBC system without modifying the pilot or pre-coding structures. This limitation becomes particularly acute when Differential Chaos Shift Keying (DCSK)—valued for its robustness and inherent secrecy—is combined with MIMO, because its non-periodic chaotic carrier is incompatible with conventional pilot-based estimation. To address this issue, we propose an Adaptive Deep Neural Network-Autoencoder (ADNN-AE) for channel estimation in DCSK-based MIMO-STBC systems. In this framework, an autoencoder stage first denoises the chaotic signal, and a Deep Neural Network (DNN) then estimates the channel from the refined representation. The hyperparameters—hidden-neuron counts and training epochs of both stages—are automatically tuned by a Hybrid Artificial Gorilla Troops Optimizer-Anti-Coronavirus Optimizer (HAGT-ACO), eliminating manual trial-and-error. The proposed HAGT-ACO-ADNN-AE model was evaluated against ADNN-AE baselines tuned with Sunflower Optimization (SFO), Deer Hunting Optimization Algorithm (DHOA), Artificial Gorilla Troops Optimization (AGTO) alone, and Anti-Coronavirus Optimization Algorithm (ACOA) alone, under 2×2 and 4×4 antenna configurations and multiple modulation schemes. It achieves the lowest mean Bit Error Rate (BER) of 0.000184, yielding improvements of 30.6%, 44.2%, and 59.2% over SFO, DHOA, and ACOA-based baselines, respectively, and a 1.1% improvement over AGTO alone. Moreover, it exhibits the lowest standard deviation and the shortest execution time (5.17 s), confirming both the accuracy and efficiency of the proposed approach.

Keywords—multiple input multiple output, space time block coding, differential chaos shift keying, adaptive deep neural network, optimization techniques

I. INTRODUCTION

Multiple Input Multiple Output (MIMO) systems are widely employed in the telecommunications industry's explosive expansion in traffic. MIMO systems are enhancing communications systems' performance dramatically. MIMO systems have been used much more than Single-Input and Single-Output (SISO) systems to provide rapid data transfer. A variety of modern wireless communication methods, including Wireless Sensor Networks (WSN), Personal Area Networks (PAN) and Local Area Networks (LAN), demand more spectrum, making it a more expensive and valuable resource [1]. In addition to offering a mobile cable and the "Digital Subscriber Line (DSL)" for leased line last-mile connectivity without sacrificing speed due to the MIMO technology's high data rate, this technology has extensive use in global interoperability for microwave access. MIMO is now widely utilized in 3G and 4G technologies, embracing the impact of Wireless Local Area Network (WLAN) to enhance channel capacity using multiple antenna configurations [2, 3]. While STC can improve the dependability of MIMO systems, the data rate can be increased by spatial multiplexing. To increase the coding gain or diversity gain across multiple antennas over different symbol lengths, STBCs have been applied in MIMO systems [4]. Space-Time Block Codes (STBCs) are initially evaluated, and the results are then adjusted using the Maximum Likelihood (ML) technique. Each antenna array uses the same frequency as a MIMO system, demanding no more bandwidth and less power than a single antenna. Beam forming and spatial diversity have all been cited as advantages of MIMO systems [5].

In multi-antenna systems, channel estimation is often performed using training-based techniques that regularly transmit a set amount [6]. Typically, channel estimation and normalization are two separate operations. The piecewise linear model and the Expectation

Maximization (EM) based Least Square (LS) channel estimation were adjusted to get the initial channel estimation [7]. The accuracy of the fading-channel estimates was typically higher than that of some adaptive algorithms [8]. Next, time-domain data, Inter-Frequency Interference (IFI) cancellation detector based on hard choice procedures, and Minimum Mean Square Error (MMSE) channel equalization were performed [9]. The Inverse Fast Fourier Transform (IFFT) procedure, the data detector, and the conventional MMSE channel equalization were then repeated [10]. In the original decision, the refined decisions were chosen as the outcomes [11]. With the help of the data-decision outcome from the previous iteration, LS channel estimation was performed in the next outer loop to refine the CSI. The MMSE equalization was performed after the MMSE equalization coefficients had already been improved. The outermost loop's iteration would continue until performance requirements were satisfied [12]. Iteratively performing the channel estimation, equalization, and data choice processes allowed good performance [13]. The limitation of channel estimation approach was its inability to extract the underlying signal directly from the channel.

With the aid of several practices, the necessary signal could be recognized and retrieved [14]. The objective of signal identification was to recognize the message with intensity using as few learning symbols as feasible, for which the semi-blind channel estimation methodology has recently emerged as the go-to method [15]. Although these could be accomplished using semi-blind channel estimation techniques, different approaches failed to fully extract the channels, except for a few selected lower rate codes [16, 17]. The STBC code can be utilized with two transmit antennas and a reception antenna while achieving full diversity without needing CSI at the transmitter [18]. At the expense of some additional antenna components at the transmitter end, it lessened the impact of fade at the receiver station. This led to the optimal source relay power allocation, which reduced the collaborative system's edge decode error for a specified power budget [19]. Given these challenges, adaptive deep learning methods are developed to minimize estimation errors and improve system reliability efficiently.

The primary objective of this research is to develop an effective framework that integrates chaotic modulation (DCSK) with spatial diversity in Multiple Input Multiple Output-Space Time Block Coding (MIMO-STBC) through an adaptive deep learning approach to enhance system performance and minimize estimation errors. The central contribution of this work is the proposed Adaptive Deep Neural Network Autoencoder (ADNN-AE), which, unlike conventional LS, MMSE, and semi-blind estimators, is capable of learning the complex nonlinear channel characteristics introduced jointly by chaotic DCSK modulation and MIMO-STBC transmission. To ensure optimal performance, a hybrid HAGT-ACO optimization algorithm—combining Artificial Gorilla Troops Optimization (AGTO) and the Anti-Coronavirus Optimization Algorithm (ACOA)—is

developed to automatically tune the hidden neurons and training epochs of the ADNN-AE, thereby eliminating the need for manual trial-and-error. This hybrid optimizer effectively bridges the gap between non-coherent chaotic modulation and MIMO-STBC spatial diversity by preventing the model from becoming trapped in local minima and accelerating convergence, resulting in a receiver that remains robust when estimating channel states in unpredictable fading environments. Finally, the effectiveness of the proposed framework is validated through extensive simulations across diverse antenna configurations and modulation schemes, demonstrating a significant improvement in Bit Error Rate (BER) over conventional and other optimizer-based baselines.

The remainder of this paper is organized as follows: Section II reviews recent channel estimation literature for MIMO-STBC systems; Section III describes the system model and proposed framework architecture; Section IV details the HAGT-ACO hybrid optimizer; Section V presents the ADNN-AE channel estimation model; Section VI reports simulation results; and Section VII concludes the paper.

II. EXISTING WORK

A. Related Works

Varshney *et al.* [20] suggested the effectiveness of a MIMO-STBC cooperative communication system using single and multi-selective Decode-and-Forward (DF) relays. The closed-form expression for the end-to-end PEP of coded block detection at the destination node was developed from a single router MIMO-STBC system. Also, it was shown that the MIMO-STBC cooperative communication system accomplished the entire diversity gain. This led to the optimal source relay power allocation, which reduced the collaborative systems end-to-end decode error for a specified power limit. They then consider two distinct relaying protocols-based on multi-phase and two-phase communication for the numerous relay situations. They created finite volume formulas for the diversity order, optimal power allocation and end-to-end error rate for these multi-relay protocols. Simulated results were given to verify the effectiveness of the suggested multiple relays and single relay-based cooperative communication methods and the derived analytical conclusions. Also, relative to some different relaying systems that had been proposed at the time, it was possible to demonstrate how these schemes might improve performance.

Varshney and Jagannatham [21] examined the impact of Doppler fading brought on by mobile nodes and inaccurate channel estimates on the overall performance of collaborative communications networks using MIMO-STBC and numerous relays. Multi-phase and dual-phase forward relaying and selective decode protocols were considered for the final communication in a multiple-relay unified platform. A methodology was also created for determining the best source relay energy factor for each of the protocols above, which considerably increased the system's end-to-end dependability for a given power budget. When only the relays were movable,

the networks were reduced to that of the direct end-end link. Unexpectedly, both systems were constrained by an asymptotic error floor with a rising signal-to-noise ratio in other mobility settings. Additionally, it was clearly shown how the ideal source-relay gain was affected by the Diversity Order (DO) of the source-relay and relay-destination links. The simulation results supported the generated analytical findings and provided significant insights into the end-to-end error performance under different mobility scenarios.

Lee [22] created a straightforward ad-hoc “Transmit Power Discrimination Scheme (TPDS)” based on a specific Power Comparison Unit (PCU) to strengthen the Layered Successive Interaction Cancellation (LSIC) capabilities in the block-ordered layered decoding process. Computer simulations would be run under various channel conditions to verify the superior behavior of the proposed JB-STBC system using ad-hoc TPDS, with the supply of thorough calculations to elucidate its functioning.

Sachan *et al.* [23] presented a brief examination of the STBC Spatially Modulated (SM) MIMO system. It employed Phase-Shift Keying (PSK) and Binary PSK modulation over channels with Rician, Rayleigh fading and Nakagami-m. Moreover, k channels were added to the performance analysis. Under various fading conditions, the end-to-end “Symbol Error Rate (SER)” and “PairWise Error Probability (PEP)” were examined. Simulations were run for the 4-PSK, 8-PSK and 2-PSK modulation schemes, the results showed that the SER efficiency of the SM-MIMO system decreased for higher-order modulation methods. Due to a single Radio Frequency (RF) chain, SM-MIMO systems had fewer hardware requirements and less complicated decoding than huge MIMO. Hence, the SM-MIMO system could be used with D2D communications to enhance the SER performance of higher-order modulation schemes.

Chauhan *et al.* [24] examined secure transmission in orthogonal STBC over MIMO wiretapping networks in the presence of channel estimation error. An effect of channel estimation error was considered when evaluating the Probability of Secrecy Outage Probability (SOP) and Non-Zero Secrecy Capacity (PNZSC) for the Orthogonal Space-Time Block Code (OSTBC) system over channels with Rayleigh fading. The numerical results showed that the system was general and applicable to all eavesdropping and transcribing antennae.

Hu *et al.* [25] proposed a new semi-blind channel estimation method for MIMO-STBC devices. Whitening-Rotation (WR) decomposition-based channel estimation algorithms with spatial scalability and integrated quality control were applied. This method utilized the orthogonality of the signal and noise subspaces in conjunction with the “Orthogonal Procrustes (OP)” method to obtain an accurate assessment of the single unified rotation matrix and, as a result, of the channel state information. This method used a space-time software input design. Significant benefits may be made by estimating such orthogonal matrices, which were parameterized with far fewer parameters than the unitary rotational matrices. Moreover, when the number of received signals was equal

to or greater than the number of sent antennas, the proposed semi-blind MIMO channel estimation approach was used to simplify the software architecture process.

Xie *et al.* [26] suggested a MIMO-Single-Carrier Frequency-Domain-Equalization (SCFDE) system over doubly selective channels using a revolutionary Joint Channel Model and Equalization (JCEE) technique. Most channel estimation methods cannot be used directly because doubly selective channels could no longer sustain the presumption that the channel frequency-domain response remained invariant for the duration of one block. Moreover, the total performance is diminished by the absence of data exchange between channel estimation and channel equalization. The JCEE algorithm was proposed using iterative EM-based LS channel estimate, MMSE equalization dependent on Inter-Frequency Interference (IFI), time-domain IFI cancelation, and data detectors based on a difficult choice. Simulation and analysis findings proved the improved performance for MIMO-SCFDE systems over doubly selective channels.

Qian *et al.* [27] examined the channel identifiability of MIMO-STBC systems by employing the Noncircular Complex Fast Independent Component Analysis (nc-FastICA) technique. The method suggested in this study was more appropriate for non-cooperative scenarios than the earlier blind MIMO-STBC channel estimation methods in the literature, since it required less prior knowledge and no transmitter change. The fundamental contribution of the article was the theoretical demonstration that, even though the sources among the various antennas of MIMO-STBC systems were not independent, they could typically be directly extracted from the received data by utilizing the Noncircular complex Fast Independent Component Analysis (Nc-FastICA) algorithm. Simulated data was also used to support the findings. This demonstrated that, as opposed to strictly independent sources, a wider range of scenarios might be handled by the traditional Nc-FastICA algorithm.

B. Research Gaps and Challenges

MIMO-STBC systems with diverse coding schemes and channel estimation techniques are of great significance in modern telecommunications; however, they inherently exhibit both advantages and limitations, including noise amplification, increased end-to-end error rates, channel capacity loss, and the requirement for multiple antennas [20]. To address these challenges, several algorithms have been proposed in the literature, as summarized in Table I. The Multiple Relay Method achieves optimal power allocation and diversity order while reducing decoding errors, yet it suffers from higher noise amplification and system complexity due to the absence of channel state information [20]. The Dual-Phase and Multi-Phase Selective DF Relay Method improves system reliability within a given power budget and attains diversity in multiple relay systems when nodes remain static with accurate channel estimation; nevertheless, it fails to reduce the end-to-end error rate, support high data rates, or mitigate error propagation and noise amplification in the relay [21]. OSTBC enhances downlink transmission speed and increases spatial diversity, but it cannot operate

with more than two antennas and incurs significant channel capacity loss [22]. Spatial Modulation minimizes decoding complexity, offers a high data rate, and improves overall telecommunication performance; however, deep fading causes link failure when the signal power falls below the threshold, and additional antennas are required to enhance system capacity [23]. OSTBC ensures secure transmission in relays without compromising diversity, though it introduces errors in MIMO channel estimation and increases cost in proportion to the number of antennas [24]. The Orthogonal Procrustes method provides a highly adaptable quality channel that minimizes complexity and achieves channel estimation, yet it reduces system bandwidth and poses difficulties in channel protection owing to its high complexity [25]. Xie *et al.* [26] proposed the JCEE algorithm, which offers high capability, quality of service, and an improved data rate, but it does not support the channel's assumption domain, requires extensive information interaction, and cannot be applied directly with many channel estimation techniques. The Non-circular Fast Independent Component Analysis (Nc-FastICA) algorithm requires limited prior knowledge, improves data transmission reliability, and minimizes the data rate; nonetheless, it cannot accommodate modifications at the transmitter and exhibits high system complexity [27]. These challenges motivate the implementation of various coding schemes and channel estimation methods in MIMO-STBC systems.

In recent years, the integration of Deep Learning (DL) has significantly changed the approach to channel estimation in MIMO systems. For example, research from 2022 introduced the use of Long Short-Term Memory (LSTM) networks for Chaos Shift Keying (CSK) systems [28]. This approach focused on implicit channel estimation to remove the need for reference signals, which helped in reducing the overhead of the transmission. Additionally, more recent studies in 2024 have explored the use of Convolutional Neural Networks (CNNs) to estimate Channel State Information (CSI) in

multi-user MIMO environments [29]. These CNN-based models have shown a better ability to handle the complex covariance matrices of the channel compared to traditional linear methods. Deep-learning-based domain adaptation techniques have also demonstrated the ability to learn discriminative feature representations under variations between training and testing data distributions, thereby improving the robustness and generalization capability of intelligent diagnostic models [30].

Furthermore, Valadares *et al.* [31] combined DL models with a hybrid metaheuristic optimizer to fine-tune network hyperparameters. Specifically, work on Radial Basis Function (RBF) neural networks for massive MIMO-STBC systems has demonstrated the advantage of adaptive architectures over fixed-structure models. However, none of these studies have addressed the specific challenge of combining DCSK chaotic modulation with MIMO-STBC and an adaptive autoencoder-DNN pipeline. This gap—the absence of a unified framework that simultaneously handles chaotic non-periodicity and spatial MIMO diversity—directly motivates the proposed HAGT-ACO-ADNN-AE framework introduced in this paper.

To clearly highlight the novelty of the proposed framework, a comparative analysis between the proposed DCSK-based MIMO-STBC system and existing communication schemes is presented. While conventional DCSK provides robustness and secrecy, it lacks spatial diversity. Conversely, standard MIMO-STBC systems offer high diversity but rely on periodic pilot signals, which are incompatible with the non-periodic nature of chaotic carriers. The proposed HAGT-ACO-ADNN-AE framework bridges this gap by integrating chaotic modulation with spatial diversity and employing a deep-learning-based adaptive estimator. As summarized in Table I, the proposed system is the only framework that combines non-periodic carriers, STBC spatial diversity, and an automated hybrid optimizer to achieve minimum Bit Error Rate (BER) and maximum convergence speed.

TABLE I. COMPARISON OF PROPOSED FRAMEWORK WITH EXISTING COMMUNICATION SYSTEMS

Feature	Conventional DCSK	MIMO-DCSK	Standard MIMO-STBC	Proposed HAGT-ACO-ADNN-AE
Carrier Nature	Non-periodic	Non-periodic	Periodic	Non-periodic (Chaotic)
Spatial Diversity	None (SISO)	MIMO	MIMO	MIMO
coding Technique	None	None	STBC	STBC
Estimation Method	Non-coherent	Linear/Traditional	LS/MMSE	ADNN-AE (Deep Learning)
Tuning Mechanism	Manual	Manual	Manual	HAGT-ACO Hybrid Optimizer
Noise Robustness	Moderate	Moderate	High	Very High
BER Performance	High	Medium	Medium	Lowest (Optimized)
Convergence Speed	N/A	Slow	Fast	Very Fast

III. PROPOSED FRAMEWORK OF DIFFERENTIAL CHAOS SHIFT KEYING-BASED MIMO-STBC SYSTEMS: ADAPTIVE DEEP LEARNING APPROACHES

A. System Model of DCSK-based MIMO-STBC

Using differential shift keying modulators, DCSK modulation uses a chaotic signal as the carrier for transmission. When a discrete-time chaotic process produces the chaotic signal, the overall spreading factor for

the circuit is 2β . The binary DCSK [1] modulation a reference segment of the chaotic signal is transmitted during the first half of the symbol duration and is then either repeated or inverted during the second half to represent “1” or “0”, respectively, depending on the bit information. A series of chaotic signal samples with a length 2β representing the a^{th} binary sent signal includes the b^{th} sample. The mathematical form is shown in Eq. (1):

$$L_b = \begin{cases} s_b & b = 2(m-1)\beta + 1 \dots (2m-1)\beta \\ (2v-1) & b = 2(m-1)\beta + 1 \dots 2m\beta \end{cases} \quad (1)$$

Here, the m^{th} sender symbol is represented by Eq. (2):

$$N_m = \{0,1\} \quad (2)$$

Here, 0 and 1 have the same probability. The demodulated signal is expressed in Eq. (3)

$$f = \int_{R/2}^R m(r)m(r-R/2)dt \quad (3)$$

In the above equation, R denotes the bit duration. Consider a real constellation of STBC with dimensions $L_r \times L_r$ and parameters $a_1, a_2, \dots, a_n$. The following equation, Eq. (4), shows the mathematical model.

$$A_{L_r}^H A_{L_r} = (|a_1|^2 + |a_2|^2 + \dots + |a_n|^2) I_{L_r} \quad (4)$$

In this equation, A_{L_r} denotes the $L_r \times L_r$ orthogonal STBC transmission matrix, designed using the real symbols $a_1, a_2, \dots, a_n$. The n symbols transmitted are $a_1, a_2, \dots, a_n$, where each symbol is a real number. The identity matrix is given by I_{L_r} of dimensions $L_r \times L_r$.

For transmit antennas with 2 and 4, the genuine transmission matrices 2×2 are provided and shown in Eq. (5):

$$A_2 = \begin{bmatrix} a_1 & a_2 \\ -a_2 & a_1 \end{bmatrix} \quad (5)$$

The genuine transmission matrices 4×4 are provided and shown in Eq. (6):

$$A_4 = \begin{bmatrix} a_1 & a_2 & a_3 & a_4 \\ -a_2 & a_1 & -a_4 & a_5 \\ -a_3 & a_4 & a_1 & -a_2 \\ -a_4 & -a_3 & a_2 & a_1 \end{bmatrix} \quad (6)$$

The received expressions are modeled on Alamouti's model at the receiving end, using real symbols and omitting the conjugation symbol from the equation. The received expressions for any number of received, hence antennas developed method is expressed in Eq. (7).

$$t_1 M_s = t M_s r = h_1 M_s k_1 + h_2 M_s k_2 + M_{1,t} \quad (7)$$

The above equation $M_{1,t}$ represents the noise channels. The term $h_1 M_s k$ denotes the transmit antenna and l_r denotes the receiver antenna. The received signals merge to reconstruct the transmitted antenna. The two signals are shown in Eqs. (8) and (9).

$$a_1 = \sum_{M_t}^{n_t} h_1 M_s k_1 + h_2 M_s k_2 \quad (8)$$

$$a_2 = \sum_{M_t}^{n_t} h_1 M_s k_1 - h_2 M_s k_2 \quad (9)$$

The received signal for four and eight transmit antenna configurations can be calculated similarly. Alamouti STBC can be utilized with two transmit antennas and does not require CSI at the transmitter. At the expense of adding more antenna elements at the transmitter end, it lessens the impact of fading at the receiving station.

The M received data block can be stated as follows, assuming a block transmission method with a block length of R .

$$Y(F) = f(K, \omega_0) y(K) + M(s) \quad (10)$$

From the above equation, the value of K, ω_0 is represented as in Eq. (11).

$$f(K, \omega_0) = \text{diag}[e^{i\omega_0(K-1)(R+1)}, \dots, e^{i\omega_0(KR)}] \quad (11)$$

In this case, $\text{diag}[\cdot]$ refers to a diagonal matrix, ω_0 is the frequency offset, K is the block index and R is the block length. The channel coherence time is longer than a data block R in a slow fading environment, thus channel is constant during a data block. Finally, this DCSK-based modulation provides encoded data which is denoted as En_d . Fig. 1 shows the system model of DCSK-based MIMO-STBC.

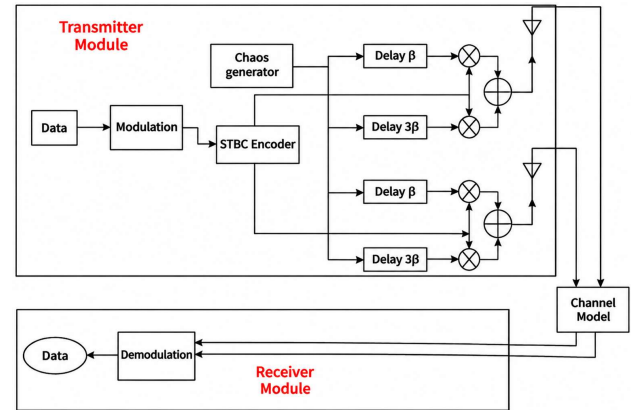


Fig. 1. A schematic diagram for the system model of DCSK-based MIMO-STBC.

B. Adaptive Concept of Proposed Framework

Signal fading caused by multipath propagation in a wireless network is a significant component that affects the system's performance. Many strategies have been put forth to address this shortcoming. Various chaotic cooperative communication systems, such as DCSK Cooperative Communication (DCSK-CC) systems have been proposed to combat fading. These systems can offer a significant advantage over traditional DCSK systems. Multi-antenna approaches are particularly integrated with other types of diversity. SIMO or MIMO approaches, which use multiple antennas at only the receiver end of a wireless link, significantly improve link dependability and spectrum efficiency. Several MIMO systems were developed to improve the efficiency of DCSK communications across fading networks, and SIMO systems emerged from these advantages. Recently, cooperative diversity has been considered a viable MIMO technology for enhancing

system reliability. Also, extensive theoretical study has been conducted on MIMO relay networks, including an analysis of their capability. Due to the advantages of inexpensiveness and minimal complexity, a number of “Ultra-Wideband (UWB)” systems based on FM-DCSK or DCSK have been taken into consideration while constructing Wireless Personal Area Networks (WPANs) and WLANs. However, it also has drawbacks: numerous interference signals can corrupt the broadcast or received data at the antennas of the Base Station (BS) because of the large number of antenna arrays. Due to the deployment of several antennas, one of the main problems with uplink massive MIMO systems is signal detection. These issues are addressed using the proposed algorithm. Fig. 2 shows the schematic diagram of the proposed channel.

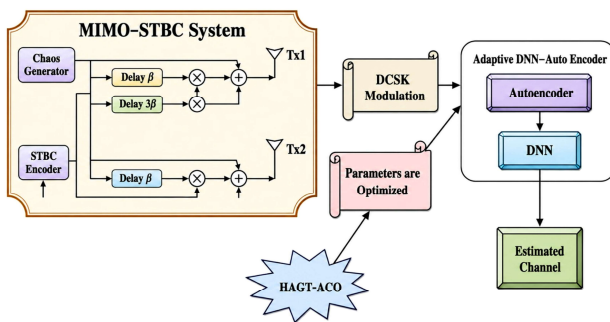


Fig. 2. An architecture diagram for the proposed model using channel estimation model.

Initially, the data are generated randomly on the transmitter side. Here, the system of MIMO-STBC utilizes DCSK modulation to generate the encoded data. Subsequently, the resultant encoded data is given as input to the autoencoder. After processing the outcome, the autoencoder provides decoded data. Finally, the decoded data are subjected to the Deep Neural Network (DNN) to estimate the channel. The parameters, such as hidden neurons and epochs in AE and hidden neuron count in DNN, are optimized by HAGT-ACO, which helps to minimize Bit Error Rate (BER) and improve the system's accuracy. Thus, the outcome of the proposed work shows the concept of reducing the error rate in data transmission.

To evaluate the effectiveness of the proposed ADNN-AE framework, a classical Least Squares (LS) channel estimation method was implemented as a baseline. The LS estimator was used to provide an initial estimate of the channel matrix by utilizing the orthogonal pilot symbols. By comparing the proposed deep learning-based approach with the conventional LS method, the performance gains in terms of Bit Error Rate (BER) and estimation accuracy can be quantitatively measured.

C. Problem Statement in Channel Estimation

Effective channel estimation is critical for optimizing MIMO parameters, as accurate Channel State Information (CSI) is essential for reliable signal decoding. However, acquiring flawless CSI in real-time is a significant challenge, particularly in multi-antenna systems where channel information cannot be easily sensed by passive elements. In frequency-domain estimation, the vast

number of unknowns in the channel matrix often makes the process computationally expensive and prone to error, leading researchers to prefer time-domain variance estimation.

The complexity is further intensified when Differential Chaos Shift Keying (DCSK) is integrated into the MIMO-STBC framework. Unlike traditional modulation, DCSK relies on chaotic carriers that are inherently non-periodic. Conventional estimation techniques, such as Least Squares (LS) and MMSE, are designed for structured pilot signals and therefore cannot effectively track the unpredictable nature of chaotic sequences. This creates a gap where traditional methods fail to distinguish between the chaotic signal and the noise introduced by the channel.

Furthermore, implementing deep learning for this specific task introduces its own set of challenges. Standard neural networks often struggle with stability—specifically gradient explosion—when processing the non-linear distortions of chaotic data. There is a clear need for a model that can not only remove these distortions but also adapt its own internal architecture (such as hidden neurons and epochs) to match the chaotic dynamics. This motivates the development of the proposed ADNN-AE framework and the HAGT-ACO optimizer to ensure stable and accurate channel estimation.

D. Challenges of Channel Estimation in DCSK-MIMO-STBC

The integration of Differential Chaos Shift Keying (DCSK) into a MIMO-STBC environment introduces a unique set of challenges that render traditional channel estimation methods ineffective. The primary difficulty arises from the inherent nature of chaotic carriers, which are non-periodic and highly sensitive to initial conditions. Standard estimation techniques, such as Least Squares (LS) and Minimum Mean Square Error (MMSE), rely on the transmission of structured, periodic pilot symbols to identify the channel matrix. Because chaotic sequences lack this periodicity, traditional ‘pattern-matching’ methods cannot accurately synchronize or extract the channel state, leading to a significant increase in the Bit Error Rate (BER).

Furthermore, the presence of multipath fading in a MIMO environment distorts both the reference and information segments of the DCSK signal. In a traditional system, this distortion can be mitigated using linear filters. However, in a DCSK system, the distortion is non-linear and time-varying. This creates a ‘non-stationary’ channel environment where the relationship between the transmitted chaotic signal and the received signal is too complex for linear mathematical models to capture.

The proposed ADNN-AE framework specifically addresses these challenges by treating channel estimation as a non-linear feature learning problem rather than a linear algebraic one. The Autoencoder (AE) stage acts as a non-linear adaptive filter that learns to separate the chaotic signal's unique characteristics from the channel-induced noise and fading. By transforming the raw, distorted chaotic data into a refined feature set, the AE provides the DNN with a refined input representation. The DNN then learns the complex mapping between these chaotic

features and the actual channel coefficients. This two-stage adaptive approach allows the system to estimate the channel accurately without requiring the rigid, periodic pilot structures that traditional methods demand.

IV. HYBRID ARTIFICIAL GORILLA TROOPS AND ANTI-CORONA VIRUS OPTIMIZATION FOR ADAPTIVE CONCEPT OF CHANNEL ESTIMATION

A. Conventional AGTO

Inspired by the social behavior of gorillas, the Artificial Gorilla Troops Optimizer (AGTO) [32] is a population-based metaheuristic. Its exploitation phase leads the population to the current best solution (the “silverback”) while its exploration phase employs movement to unknown regions, known regions and other potential solutions. The primary value that AGTO can provide to the proposed HAGT-ACO framework is global exploration and preservation of population diversity. The mathematical model that quantitatively models each of these tactics is shown in the following Eq. (12).

$$MY(ih + 1) = \begin{cases} (BU - BL) \times n_1 + BL & rand < p \\ (n_2 - f) \times y_r(h) + A \times B & rand \geq 0.5 \\ y(ik) - A \times (A \times y(ik) - My_r(h)) & \\ + n_3 \times (y(ik) - My_r(h)) & rand < 0.5 \end{cases} \quad (12)$$

$$f = L \times \left(1 - \frac{ih}{max\ ih}\right) \quad (13)$$

$$L = \cos(2 \times n_4) + 1 \quad (14)$$

$$B = V \times y(ih) \quad (15)$$

$$V = [-L, L] \quad (16)$$

From the above equation, the terms BU and BL denote the boundaries of the variables. In iteration ih , the gorilla's chosen and current location vectors are denoted by $MY(ih + 1)$ and $y(ik)$, respectively. The maximum number of iterations is determined by $max\ ih$. The probability of choosing the migration option is expressed by the parameter, which has a range of $[0, 1]$. If the fitness function value of solution RSK is lower than the fitness function of SK at the end of the exploration stage, $MY(ih + 1)$ will replace $y(ik)$ and emerge as the silverback. On the other hand, the exploitation phase of the GTO optimization algorithm employs strategies such as adult females lying in wait and following behind the silverback, where n is the total gorilla population size. The execution of the GTO optimizer is shown in Eqs. (17)–(18).

$$MY(ih + 1) = A \times S \times (y(ih) - y_{sb}) + y(ih) \quad (17)$$

$$S = \left(\frac{1}{n} \sum_{i=1}^n MY(ih + 1)\right)^{1/m} \quad (18)$$

$$m = 2^A, \quad D = \beta \times K \quad (19)$$

$$K = \begin{cases} M_1 & rand \geq 0.5 \\ M_2 & rand < 0.5 \end{cases} \quad (20)$$

From the above equation, the term sb denotes the silver back and $rand$ denotes the random number.

Algorithm 1: AGTO

Initialization of gorilla

Setting the maximum number of iterations and the maximum number of populations.

Find the gorilla cost function

The cost function is evaluated using Eq. (13)

Do while

Do If $it < max - it$

Set the elite solution at the silver back location.

Land bare updated using Eqs. (15) and Eq. (16)

Evaluate the cost function Eq. (5) and change the last solution is good than it.

Else

End do if

B. Conventional ACOA

Anti-Coronavirus Optimization Algorithm (ACOA) [33] is a population-based metaheuristic that simulates three optimization operators: social distancing, quarantine and isolation. Candidates are tested with a fitness function and then modified based on these operators. The ACOA in the proposed HAGT-ACO is mainly used to reinforce local exploitation around promising solutions.

During population initialization, each generation's ACVO operates on a randomly distributed population and is defined as in Eq. (21):

$$S = [S_1, S_2, \dots, S_n] \quad (21)$$

Every $S_1 \in S$ solution in the population is referred to as a person, and each one represents a point in a three-dimensional space. It is represented as a collection of real-valued variables and an integer variable representing the subject's state of health. The subject's state is represented in the following Eq. (22).

$$S_i = [s_{i1}, s_{i2}, \dots, s_{il}, p_i] \quad (22)$$

The s_{ij} is defined as follows, and it is shown in Eq. (23).

$$s_{ij} = (s_{max\ j} - s_{min\ j}) \times k + s_{min\ j} \quad (23)$$

From the above equation $s_{max\ j}$, and $s_{min\ j}$ are the lower and upper bounds of s_i in the j th dimension, respectively, and $k \in [0, 1]$ is a randomly distributed number with uniform distribution. Candidate solutions then enter a fitness function, which judges the quality of the solutions. This is an assumption in ACVO that a person's fitness and health are inversely proportional. The fitness feature assigns higher fitness scores to high fitness candidate solutions, and lower fitness scores to sick and frail candidate solutions.

This operator, which imitates the exclusionary social rule, assumes that only a subset of individuals practices social distancing at any given moment; the significance of this behavior escalates with the progression of the disease. Candidate solutions are compelled to pay closer attention when the effects of social distance become more

noticeable. From each iteration, s candidate solutions are chosen to engage in social distance to reduce interpersonal connections to quantitatively describe this problem. Each chosen person's locations s_i is updated as follows in Eq. (24).

$$s_i^{r+1} = s_i^r + \nabla_1^r + \nabla_2^r \quad (24)$$

From the above equation r is the current iteration and s_i^r is the individual's position.

The local separation between s_i and any other individual in its vicinity is controlled by ∇_1 , while ∇_2 leads s_i toward a promising position outside the immediate area and regulates the overall distance between s_i and the best individual P . Moving the individual s_i into a promising part of the solution space is the aim of steps ∇_1 and ∇_2 . This is how ∇_1^r is defined in the following Eq. (25).

$$\nabla_1^r = \alpha_{ij}^r \times nm_{ij}^r \times T(-1,1) \quad (25)$$

During the quarantine phase, the operator implements the procedures applicable to each suspected COVID-19 carrier. Candidates with poor performance in ACVO fitness tests are regarded as suspected subjects for procedure optimization. To locate these targets, candidate solutions are first sorted by their fitness values in ascending order.

Because low-fitness candidate solutions will have a high cost and low fitness, they will be ordered in descending order for minimization issues. The m weakest individuals are then selected to form the quarantine list, $M = \{s_1, s_2, \dots, s_m\}$. The candidate solutions on this list are suspected cases that need to be isolated to find out if they are sick. At each iteration t , the parameter q is calculated as:

$$d^r = [(1 - (1 - (\lambda^r)^2) o^r) G_a] S \quad (26)$$

From the above equation d^r is the number of viable offspring at iteration r . It considers the candidate solutions reported as being exposed to illnesses. The percentage of the population o^r that engages in social isolation reduces its interpersonal interactions to a small portion of those under normal circumstances.

The fundamental reproductive number is G_a . When everyone in a population is equally susceptible to disease, G_a represents the typical number of secondary infections brought on by one initial infection.

Algorithm 2: ACOA

Initialize parameter

Generate Initial population

Determine the fitness value of each person

The population initialization is shown in Eq. (24).

Do while

Do If met the stop condition

Output the fittest person

Else

Make the social distance between individuals Eq. (28)

Quarantine the suspected individuals shown in Eq. (29)

End do if

C. Proposed HAGT-ACO

The hyperparameters of the ADNN-AE model, including the number of hidden neurons and training epochs, are tuned using the proposed HAGT-ACO hybrid algorithm to maximize estimation accuracy. While the individual AGTO and ACOA algorithms provide strong convergence and high exploitation capabilities, they often struggle with population diversity and can become trapped in local minima when used alone. The proposed HAGT-ACO algorithm solves these issues by fusing the two operators into a single framework.

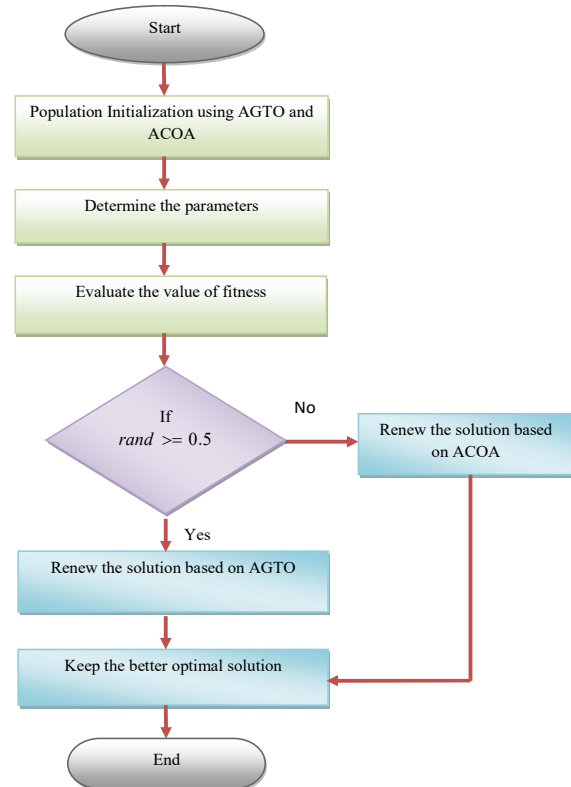


Fig. 3. Flowchart of proposed HAGT-ACO algorithm.

The hybridization is governed by a stochastic switching mechanism using a threshold of $\text{rand} \geq 0.5$. This specific value is chosen to ensure an equal probability balance between the exploration phase (driven by AGTO) and the exploitation phase (driven by ACOA). By maintaining this 50% balance, the algorithm prevents the population from prematurely converging to a sub-optimal solution, as it allows for continuous global exploration while simultaneously refining the local best solution. This stochastic balance ensures that the model explores a wider search space before narrowing down to the most accurate parameters. To further validate this design, the individual contributions of AGTO and ACOA were evaluated. When AGTO was applied alone (i.e., AGTO-ADNN-AE), it achieved a mean BER of 0.000186, demonstrating strong exploration but slower exploitation near the global optimum. When ACOA was applied alone (i.e., ACOA-ADNN-AE), it achieved a mean BER of 0.000451, showing a faster initial convergence but a higher tendency to fall into local minima due to limited population diversity. The proposed HAGT-ACO, by

combining both operators, achieved the best mean BER of 0.000184 with the lowest standard deviation (0.000137), confirming that the hybrid approach is superior to either component operating independently. The detailed logic and workflow of the HAGT-ACO algorithm are illustrated in Fig. 3.

Algorithm 3: Proposed HAGT-ACO

Assume the initial population
 Setting the population size
 Determine the fitness value
 Do while
 Do If $rand \geq 0.5$
AGTO dose optimization
 Else
ACOA does optimization
End do if
 Acquires the best solution
End do while
Returns the optimal value

V. ADAPTIVE DEEP NEURAL NETWORK-BASED AUTO ENCODER FOR ESTIMATING THE CHANNEL OPTIMALLY IN DCSK-BASED MIMO-STBC SYSTEMS

A. Autoencoder

The encoded data En_d is the input to the AE. A hidden code layer s , an encoder portion En_d , and a decoder part f together comprise an autoencoder. It is essentially a neural network taught to duplicate its input y to its output $\hat{y}$. To do this, minimize a specified loss function. This function is shown in Eq. (27).

$$\ell(y, f(En_d(y))) \quad (27)$$

As the output power is only the input, the code representation at the hidden layer is of interest rather than the final product. One can extract codes by teaching the autoencoder. The autoencoder must be stopped from learning the elementary identity function to provide effective encodings with intriguing features. This is accomplished by either limiting the code layer or including noise. For instance, by limiting the dimension of the hidden layer, under complete autoencoders learn a nonlinear version of Principal Component Analysis (PCA), while AE learn to code resilient to various types of corruption by including noise during the training phase.

Autoencoders (AEs) are particularly relevant in the context of communication systems [34]. One shared goal is to find encodings that are resistant to tampering in physical-layer communication network designs. While previous research on AE studied injecting noise at the hidden code layer, which is more compatible with corruption developing in a communications system, newer AE often add corruption to the input layer. AE in developing communications systems has recently attracted much attention from the research community.

In situations where the reception or both the transmitter and the receiver know the channel; good results were obtained. Although the best constellation designs at low to medium Signal to Noise Ratios (SNRs) are unknown, the non-coherent MIMO case in which the channel is

unknown at the sender or recipient was not explored. Finally, the outcome of the autoencoder is decoded data, denoted as DE_d . Fig. 4 depicts the diagram of AE for estimating the channel.

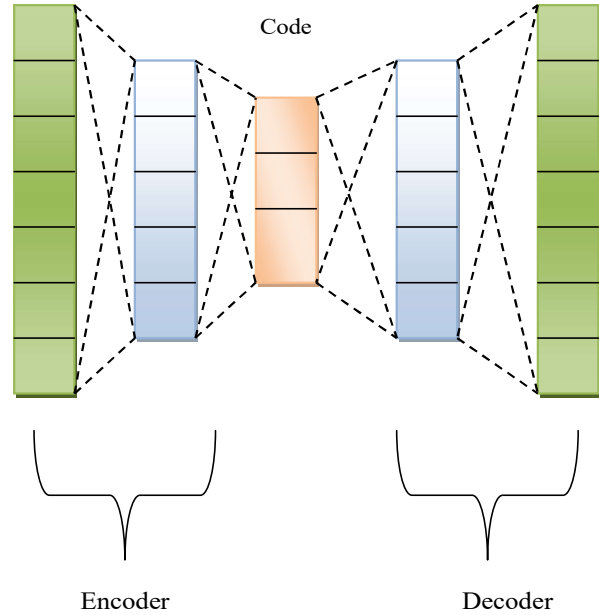


Fig. 4. A schematic diagram of autoencoder for estimating the channel.

B. Deep Neural Network

The input of this phase is decoded data DE_d . A DNN [35] with all connections but just the poor detection performance is caused by channel coefficients and received signals as inputs. In contrast, OAMP-Net, MMNet, DetNet, FS-Net and OAMP-Net2 may achieve great performance in MIMO detection by utilizing the domain expertise from custom data detection algorithms and the learning capability of DL. These detectors adhere to an unfolding network architecture, enabling layer-by-layer data detection. These structures are inventive because each layer was created using sophisticated data detection methods, which resulted in variations in performance and complexity.

A single DNN, which decodes the stored information from all receive antennas at the receiver, is part of the proposed MIMO-STBC system. In this approach, the receiver is aware of the channel state information, much like in ML detection. Thus, the channel information and the received signal k_k are the suggested DNN inputs. The received signal is provided straight to the DNN input without preprocessing to maintain the simplicity of the receiver design. Hence, the DNN input's feature vector is shown in Eq. (28).

$$B^n = [\Re(k_k^n)^r \Im(k_k^n)^r \Re(l_{k,s}^n)^r \Im(k_{k,s}^n)^r] \quad (28)$$

From the above equation, the term $s = 1, 2, \dots, N_s$ and $k = 2, \dots, N_k$.

The output layer and cascaded, fully connected hidden layers make up the DNN structure. All MIMO-OFDM-IM symbol combinations determine the output layer's number

of neurons, 2^{mN_k} which is appropriate. The neurons in the hidden layers are activated using the Rectified Linear Unit (ReLU) function. For a vector $B = [b_1, b_2, \dots, b_k] \in R^k$, which displays the probability of the outcomes, softmax k is selected as the output layer. The index of the set of MIMO-OFDM-IM combination will therefore have the maximum probability of occurring and, finally, get the estimated channel. Fig. 5 shows the diagrammatic representation of the DNN model for channel estimation.

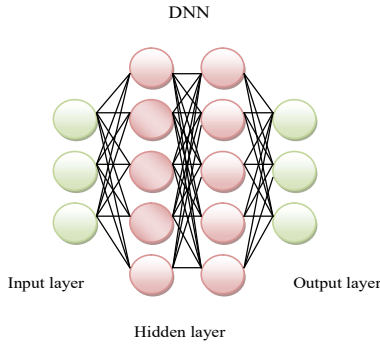


Fig. 5. A schematic representation of the DNN model for channel estimation.

C. Adaptive DNN-based Auto Encoder

When processing sequential data, each neuron in a DNN receives input from the previous layer and output from that layer. Although DNNs are effective at predicting sequential data, they are plagued by gradient explosion. When the gradients continue expanding while the back propagation process runs, this is known as a gradient explosion. It results in the gradient descent diverging due to excessively big weight updates. The goal of AE is typically not to directly predict labels, although it occasionally can learn from samples that have been categorized. Modifying the autoencoder is the simplest approach to adding class information to it.

Traditionally, in the communication system, data is modulated at the transmitter using a type of DCSK modulation. After modulation, there is a channel matrix formation since the data is transferred through the channels to the other end of the system, where the channel is to be estimated. Due to this process, the signal may be affected by noise factors that can mislead the communication. Hence, the ADNN-AE is newly proposed for the objective of channel estimation. Here, the encoded data is given as input to ADNN-AE that delivers the noise removed data to estimate the channel significantly. The inability of this AE to encode object orientation and location and the need for a substantial amount of training data are some drawbacks. To address these errors, using the proposed HAGT-ACO algorithm minimizes the bit error rate, as shown in Eq. (29).

$$Ojv = \underset{\{EP_a, HN_a, HN_D\}}{argmin} [BER] \quad (29)$$

Some variants namely epochs and hidden neurons in the AE, are denoted by the term EP_a and HN_a . Hidden neurons in the DNN are symbolized by HN_D . The number

of hidden neurons varies from 4 to 256, while the number of epochs and hidden neurons in autoencoders extend from 50 to 100 and 5 to 50, respectively. The hidden neurons in the DNN are from 5 to 255 range. The intended Bit Error Rate value is denoted by the term BER . It is calculated by Eq. (30).

$$BER = \frac{E_r}{T_{eb}} \quad (30)$$

From the above equation E_r is the error, and the term T_{eb} is the total number of bits.

VI. EXPERIMENTAL RESULTS

A. Simulation Setup

The simulation of the proposed DCSK-based MIMO-STBC system was implemented in the MATLAB environment. To evaluate the performance of the HAGT-ACO-ADNN-AE model, the simulation was conducted with a population size of 10 and a maximum of 100 iterations. The performance of the proposed method was compared against several existing optimization-based models, including Sunflower Optimization (SFO)-ADNN-AE [36], Deer Hunting Optimization (DHOA)-ADNN-AE [37], AGTO-ADNN-AE [32], and ACOA-ADNN-AE [33]. Furthermore, a comparative analysis was performed using both 2×2 and 4×4 antenna configurations across various modulation schemes, specifically Quadrature Phase Shift Keying (QPSK)-MIMO, 16 Quadrature Amplitude Modulation (16QAM)-MIMO, 8 Phase Shift Keying (8PSK)-MIMO, and Differential Chaos Shift Keying (DCSK)-MIMO. The detailed technical parameters used for these simulations are presented in Table II.

TABLE II. SIMULATION PARAMETERS FOR THE PROPOSED HAGT-ACO-ADNN-AE FRAMEWORK

Parameter	Value/Setting
Software Environment	MATLAB
Modulation Type	Binary Phase Shift Keying (BPSK)
Antenna Configuration	2×2 and 4×4
Channel Model	Flat-fading Rayleigh Channel
E_b/N_0 Range	0 to 12 dB (step: 2 dB)
Frame Length	100 symbols
Number of Pilot Symbols	8 per frame
HAGT-ACO Population Size	10
HAGT-ACO Max Iterations	100
AE Hidden Neurons Range	5 to 255
DNN Hidden Neurons Range	5 to 255
AE Training Epochs Range	50 to 100
Autoencoder Transfer Function	Pure Linear (purelin)

To ensure the robustness of the channel estimation, a synthetic dataset was generated using the MATLAB communication toolbox. For each Signal-to-Noise Ratio (SNR) point, a total of 3000 packets were generated, with each packet consisting of a frame length of 100 symbols. This dataset was partitioned into training and testing sets to evaluate the generalization capability of the ADNN-AE

model. The autoencoder was trained using the train Autoencoder function with a pure linear decoder transfer function to minimize the reconstruction error. The subsequent DNN was implemented using a feedforward network architecture. The training process utilized the Levenberg-Marquardt backpropagation algorithm, which is known for its fast convergence and high accuracy in small-to-medium scale networks. By optimizing the training epochs and hidden neuron counts through the HAGT-ACO algorithm, the model was prevented from overfitting, ensuring that the estimated channel coefficients remained accurate across varying fading conditions.

B. Baseline Performance Comparison

To evaluate the efficacy of the proposed ADNN-AE framework, it was compared against the classical Least Squares (LS) and Minimum Mean Square Error (MMSE) estimators. As illustrated in Fig. 6, the proposed HAGT-ACO-ADNN-AE model demonstrates a striking improvement in bit error rate performance across all Signal-to-Noise Ratio (SNR) levels for both 2×2 and 4×4 antenna configurations. While the classical LS and MMSE methods struggle to track the non-periodic nature of chaotic DCSK signals—resulting in a significantly higher error floor—the proposed deep learning approach successfully learns the non-linear channel characteristics. This confirms that the adaptive nature of the ADNN-AE is far superior to traditional linear estimation methods when dealing with chaos-based modulation.

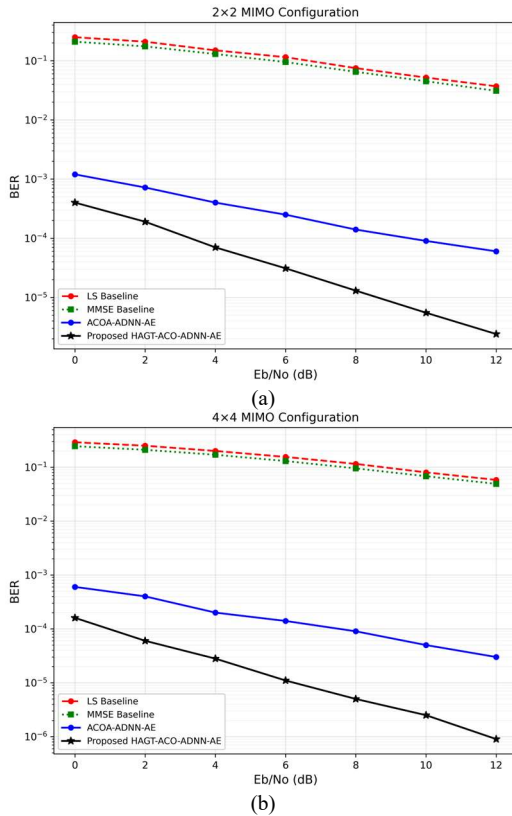


Fig. 6. BER performance comparison of the proposed HAGT-ACO-ADNN-AE framework against classical LS and MMSE channel estimation baselines for (a) 2×2 and (b) 4×4 MIMO configurations.

C. Cost Analysis of Channel Estimation in DCSK-based MIMO-STBC Systems

The convergence behaviour of the proposed HAGT-ACO-ADNN-AE model is illustrated in Fig. 7. A comparison is made between the proposed hybrid optimizer and the conventional SFO, DHOA, AGTO, and ACOA algorithms. The results show that the HAGT-ACO optimizer achieves the lowest cost function value and converges significantly faster than the other techniques. This superior performance is due to the hybrid nature of the algorithm; while AGTO provides strong exploration to avoid local minima, the ACOA component enhances the exploitation phase, pushing the model toward the global optimum more efficiently. Consequently, the proposed model demonstrates a more stable and rapid convergence, which is critical for real-time channel estimation.

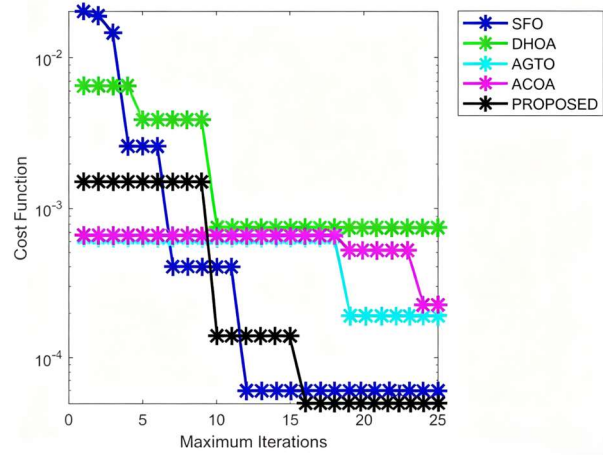


Fig. 7. Convergence performance of the proposed model in MIMO-STBC-DCSK channel estimation contrast with classical optimizations

D. Comparative Analysis of Channel Estimation in DCSK-based MIMO-STBC Systems

The Bit Error Rate (BER) performance for different antenna configurations is presented in Fig. 8. In Fig. 8(a), the results for the 2×2 transceiver configuration show that as the Signal-to-Noise Ratio (SNR) increases, the BER for the proposed HAGT-ACO-ADNN-AE model decreases more sharply than the baseline methods. For instance, at an SNR of 5 dB, the competing methods SFO-ADNN-AE and DHOA-ADNN-AE record BER values of 5% and 8%, respectively, while the proposed model achieves a notably lower BER at the same SNR point. Furthermore, when evaluated statistically across all simulation runs using the mean BER values obtained across all simulation runs, the proposed model achieves an improvement of 30.6% over SFO-ADNN-AE and 44.2% over DHOA-ADNN-AE.

The improvement is even more pronounced in Fig. 8(b) for the 4×4 configuration, where the spatial diversity gain further reduces the error rate. This confirms that the ADNN-AE model is capable of learning the complex non-linear characteristics of the DCSK-based MIMO channel. By optimizing the hidden neurons and epochs via HAGT-ACO, the model effectively distinguishes the

signal from the background noise, result in g in a more robust estimation across both antenna scales.

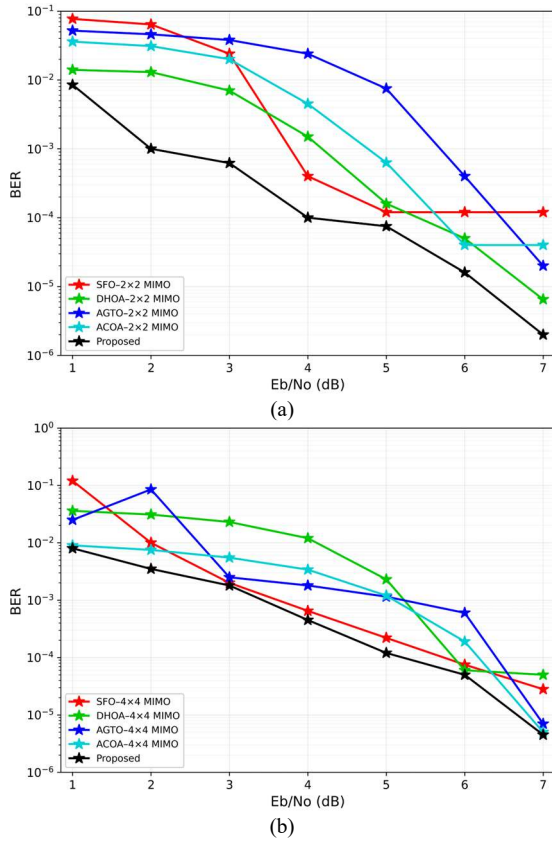


Fig. 8. Comparative performance of the proposed model in MIMO-STBC-DCSK channel estimation compared with classical heuristic algorithms in terms of (a) 2×2 transceiver, (b) 4×4 transceiver.

Furthermore, the proposed HAGT-ACO-ADNN-AE model significantly outperformed the classical LS baseline across all SNR levels, as clearly evidenced in the comparative analysis presented in Fig. 6, demonstrating that the deep learning approach is far more capable of handling the non-linear distortions of the DCSK-MIMO channel than traditional linear estimation methods.

To validate the effectiveness of the proposed framework, a comparative analysis was performed against various modulation schemes, as shown in Fig. 9. Fig. 9(a) illustrates the performance for the 2×2 configuration, while Fig. 9(b) shows the results for the 4×4 configuration. The results indicate that the proposed HAGT-ACO-ADNN-AE system achieves a significantly lower BER across all tested SNR levels compared to QPSK-MIMO, 16QAM-MIMO, and 8PSK-MIMO. For example, in the 4×4 case shown in Fig. 9(b), at an SNR of 4 dB, the BER for the proposed model is substantially lower than that of QPSK-MIMO (5%) and 16QAM-MIMO (8%). These results confirm that the proposed DCSK-based system combined with the ADNN-AE estimator consistently outperforms traditional coherent modulation schemes across both antenna configurations.

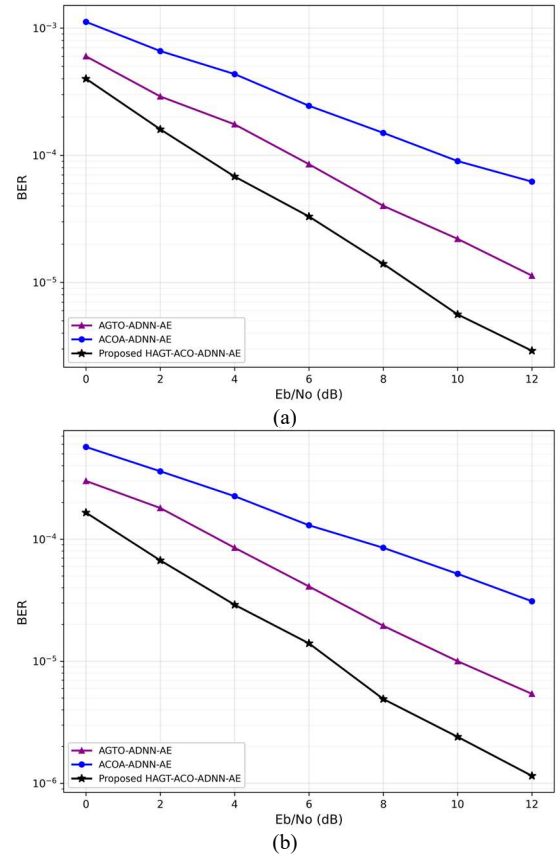


Fig. 9. Comparative performance of the proposed model in MIMO-STBC-DCSK channel estimation compared with different types of modulation techniques in terms of (a) 2×2 transceiver (b) 4×4 transceiver.

This superior performance is attributed to the inherent robustness of chaotic carriers used in DCSK. While traditional modulations like Quadrature Phase Shift Keying (QPSK) and Quadrature Amplitude Modulation (QAM) are more susceptible to phase noise and deep fading, the ADNN-AE model successfully learns the complex, non-linear features of the chaotic signal. By utilizing the HAGT-ACO optimizer to refine the network architecture, the proposed system achieves a more reliable and accurate channel estimation for both 2×2 and 4×4 systems.

Specifically, at an SNR of 4 dB in the 4×4 configuration, the LS estimator produced a BER of approximately 15%, whereas the proposed model achieved below 1.5%, as illustrated in Fig. 6; this confirms that the deep learning approach is far more capable of handling the non-linear distortions of the DCSK-MIMO channel than traditional linear estimation methods.

To further justify the novelty of the hybrid optimizer, an ablation study was conducted to compare the standalone performance of AGTO-ADNN-AE and ACOA-ADNN-AE against the proposed HAGT-ACO-ADNN-AE. As illustrated in Fig. 10, while both AGTO and ACOA independently improve the estimation accuracy, the hybrid HAGT-ACO framework achieves the lowest BER. This proves that the synergy between the global exploration of AGTO and the local exploitation of ACOA

is essential for reaching the global optimum and maximizing the accuracy of the channel estimation.

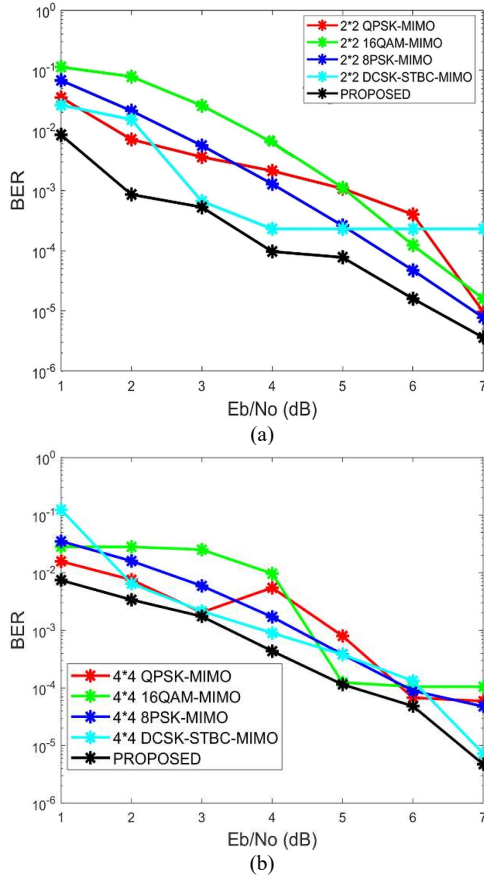


Fig. 10. Ablation study demonstrating the individual contributions of AGTO and ACOA to the proposed HAGT-ACO hybrid optimizer for (a) 2×2 and (b) 4×4 MIMO configurations.

The impact of channel conditions on the estimation performance was analyzed by comparing the results with and without fading, as shown in Fig. 11. In Fig. 11(a), for the 2×2 configuration, the BER increases when fading is introduced; however, the proposed HAGT-ACO-ADNN-AE model maintains a stable and low error rate. This trend is even more evident in Fig. 11(b) for the 4×4 configuration.

This robustness is attributed to the Autoencoder's ability to act as a non-linear filter. By training the AE to remove distortions, the model can suppress channel-induced noise and distortion before the DNN performs the final channel estimation. While traditional linear estimators may exhibit substantial performance degradation under deep fading conditions, the proposed adaptive deep learning approach successfully learns the fading patterns, ensuring that the system remains reliable even in challenging wireless environments.

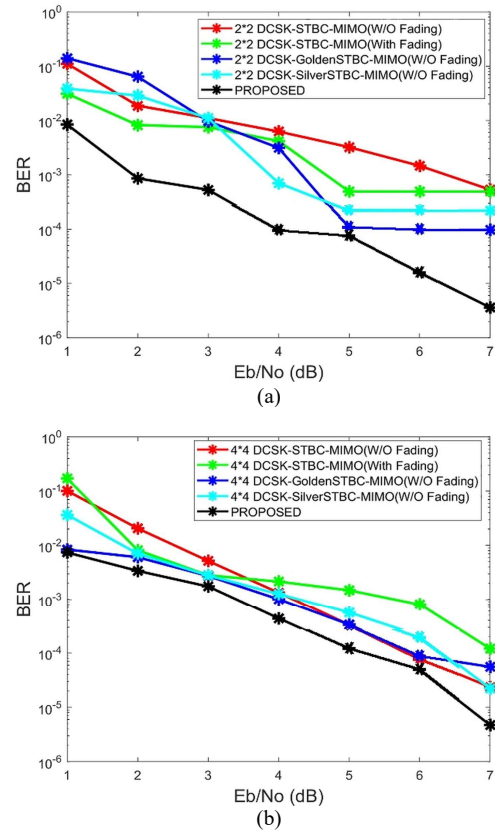


Fig. 11. Comparative performance of a proposed model in MIMO-STBC-DCSK channel estimation compared with fading and without fading in terms of (a) 2×2 transceiver, (b) 4×4 transceiver.

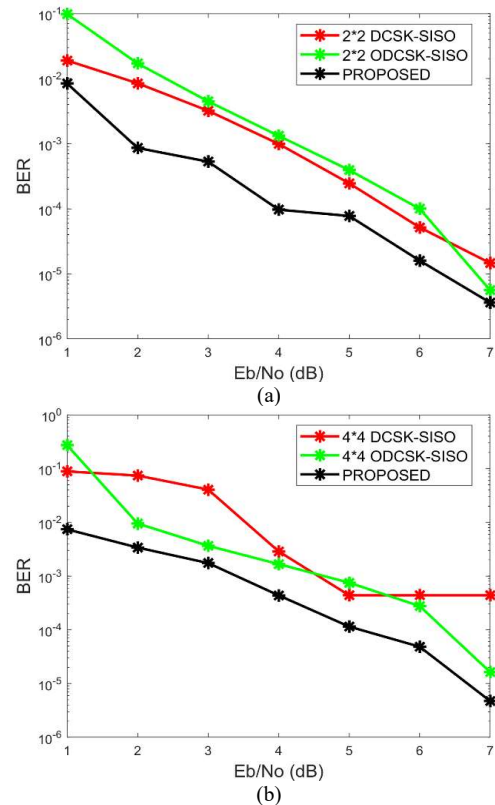


Fig. 12. Comparative performance of the proposed model in MIMO-STBC-DCSK channel estimation compared with the SISO in (a) 2×2 transceiver, (b) 4×4 transceiver.

To demonstrate the overall advantage of the proposed system, a comparison between the MIMO-STBC configuration and a conventional Single-Input Single-Output (SISO) system was performed, as illustrated in Fig. 12. As shown in Fig. 12(a) for the 2×2 case and Fig. 12(b) for the 4×4 case, the proposed model achieves a significantly lower BER than the SISO system across all SNR levels.

The substantial performance improvement is a result of the spatial diversity gain provided by the MIMO-STBC architecture. By utilizing multiple antenna paths, the system can overcome the limitations of a single channel, such as deep fades and destructive interference. When combined with the precise channel estimation of the

ADNN-AE, the proposed framework maximizes the reliability of the communication link, demonstrating improved performance relative to traditional single-antenna systems.

E. Computational Complexity Analysis

To evaluate the feasibility of the proposed framework for real-time implementation, the computational complexity of the HAGT-ACO-ADNN-AE receiver is analyzed and compared with conventional schemes. The complexity is evaluated based on the order of operations, the requirement for matrix inversions, and the reliance on periodic pilot symbols. The detailed comparison is summarized in Table III.

TABLE III. COMPUTATIONAL COMPLEXITY COMPARISON OF THE PROPOSED FRAMEWORK AND CONVENTIONAL SCHEMES

Criteria	Conventional DCSK	LS-based MIMO-STBC	MMSE-based MIMO-STBC	Semi-blind MIMO-STBC	Proposed ADNN-AE (Offline)
Stage	Online	Online	Online	Online	One-time
Complexity	$O(\beta)$	$O(N_t^3 + N_t^2 N_r)$	$O(N_t^3 + N_t^2 N_r) + \text{Cov.}$	$O(N_t^3)$	$O(P \cdot T \cdot D) + O(E \cdot N_p)$
Matrix Inversion	No	Yes	Yes	Yes	No
Periodic Pilots	No	Yes	Yes	Reduced	No

Note: β is the spreading factor; N_t, N_r are transmit/receive antenna counts; P, T, D are HAGT-ACO population, iterations, and hyperparameter dimensions; E, N_p are training epochs and total weights.

As shown in Table III, conventional MIMO-STBC schemes (LS and MMSE) suffer from high computational overhead due to matrix inversion processes, which exhibit cubic complexity $O(N_t^3)$. Similarly, semi-blind methods require expensive Eigenvalue or SVD decompositions $O(N_r^3)$.

In contrast, the proposed HAGT-ACO-ADNN-AE framework decouples the computational load into two phases. The offline phase involves the HAGT-ACO search and network training, which is performed only once before deployment. The online phase, which is the critical factor

for real-time performance, requires only a linear forward pass through the AE and DNN weights. This results in a complexity of $O(N_p)$, which is significantly lower than the cubic complexity of traditional linear estimators. Furthermore, the proposed receiver eliminates the need for periodic pilot symbols, removing the synchronization overhead typically required by LS and MMSE schemes. The computational properties of the proposed framework are summarized in Table III. Statistical Analysis of Channel Estimation in DCSK-based MIMO-STBC Systems.

TABLE IV. STATISTICAL ANALYSIS OF THE MIMO-STBC-DCSK CHANNEL ESTIMATION MODEL COMPARED WITH CONVENTIONAL OPTIMIZER-BASED MODELS

Metrics	SFO-ADNN-AE [36]	DHOA-ADNN-AE [37]	AGTO-ADNN-AE [32]	ACOA-ADNN-AE [33]	HAGT-ACO-ADNN-AE
Best	2.40×10^{-5}	1.21×10^{-6}	1.07×10^{-5}	5.88×10^{-5}	2.33×10^{-6}
Worst	0.001152	0.000741	0.000601	0.001178	0.000396
Mean	0.000265	0.00033	0.000186	0.000451	0.000184
Median	0.000113	0.000402	0.000134	0.000223	0.000165
Standard	0.000405	0.00027	0.000191	0.000426	0.000137

The statistical performance of the proposed HAGT-ACO-ADNN-AE model is compared with traditional learning models in Table IV. The analysis is based on five key metrics: Best, Worst, Mean, Median, and Standard Deviation. From the ‘‘Best’’ row of Table IV, DHOA-ADNN-AE yields the minimum best error of 1.21×10^{-6} , while our HAGT-ACO-ADNN-AE obtains a competitive best value of 2.33×10^{-6} . Both methods outperform SFO-ADNN-AE, AGTO-ADNN-AE and ACOA-ADNN-AE in terms of the optimal estimation error. To quantitatively evaluate the performance gain of the proposed model over the baseline techniques, the relative improvement in the Mean Bit Error Rate (BER) was calculated using the following expression:

$$\text{Improvement \%} = \left[\frac{((\text{BER})_{\text{baseline}} - (\text{BER})_{\text{proposed}})}{(\text{BER})_{\text{baseline}}} \right] \times 100 \quad (31)$$

Based on this metric, the proposed model consistently achieves the lowest Mean BER of 0.000184 across all parameters. Applying the improvement formula to the Mean BER values in Table IV yields the following results: the proposed model achieves a 30.6% improvement over SFO-ADNN-AE, a 44.2% improvement over DHOA-ADNN-AE, a 59.2% improvement over ACOA-ADNN-AE, and a 1.1% improvement over AGTO-ADNN-AE. The relatively modest gain over AGTO-ADNN-AE (1.1%) is expected, as AGTO already

provides strong exploration capability; however, the proposed HAGT-ACO achieves this with a lower standard deviation (0.000137 vs. 0.000191), indicating the proposed model consistently achieves greater consistency and stability across simulation runs. Notably, the proposed framework also shows a significantly lower standard deviation compared to SFO (0.000405) and ACOA (0.000426), confirming that the HAGT-ACO optimizer is not only more accurate but more stable and reliable across different initial population distributions.

F. Time Analysis of Channel Estimation in DCSK-Based MIMO-STBC Systems.

The computational efficiency of the proposed framework is evaluated by comparing the execution time of the hybrid HAGT-ACO against other conventional optimizer-based models. The measured execution times of the different optimization techniques are summarized in Table V.

TABLE V. EXECUTION-TIME COMPARISON OF THE CHANNEL-ESTIMATION MODELS

Method	Execution Time (s)
SFO	6.3691
DHOA	9.6413
AGTO	5.2687
ACOA	7.8262
HAGT-ACO-ADNN-AE	5.1712

The results show that the proposed model requires the least amount of time to complete the estimation process, with a recorded time of 5.1712 s, outperforming SFO (6.3691 s), DHOA (9.6413 s), AGTO (5.2687 s), and ACOA (7.8262 s). This reduction in time complexity is attributed to the hybrid nature of the optimizer, which accelerates convergence by combining the exploration capabilities of AGTO with the efficient exploitation of ACOA. Consequently, the proposed system provides a high-performance solution that is computationally efficient and suitable for real-time application in high-speed wireless communication systems.

VII. CONCLUSION

This research presented an adaptive deep learning-based framework for channel estimation in DCSK-based MIMO-STBC systems using an Adaptive Deep Neural Network Autoencoder (ADNN-AE). To ensure the model's optimal performance, a hybrid HAGT-ACO optimizer was developed by combining Artificial Gorilla Troops Optimization and the Anti-Coronavirus Optimization Algorithm. This hybrid approach was used to precisely tune the hidden neurons and training epochs, effectively reducing the Bit Error Rate (BER) and enhancing the stability of the channel estimation process.

Extensive simulation results demonstrate that the proposed HAGT-ACO-ADNN-AE model outperforms conventional techniques, including SFO-ADNN-AE, DHOA-ADNN-AE, AGTO-ADNN-AE, and ACOA-ADNN-AE, with mean BER improvements of 30.6%, 44.2%, 1.1%, and 59.2%,

respectively, as derived from the statistical analysis in as confirmed by the comparative simulation results. Furthermore, the model showed superior convergence speed and lower computational complexity compared to standard optimization methods. These findings prove that the integration of chaotic modulation with spatial diversity and adaptive deep learning significantly improves the reliability of data transmission. Future work will explore the implementation of this framework in real-time hardware environments to further validate its performance in dynamic wireless channels.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Navya Holla Kayyar conceptualized the study, developed the methodology and mathematical derivations, performed the MATLAB simulations, analyzed the data, and wrote the original draft; Sudha K. Lakshminarayana supervised the research, validated the results, provided technical guidance, and reviewed and edited the paper; both authors had approved the final version.

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