Design and Development of Improved Coyote Optimization-based Adaptive Equalization Technique for ECG Signal Transmission

R. Iniyavan and **B. Vijayalakshmi**†, Non-members

ABSTRACT

Biological signals such as an electrocardiogram (ECG) are broadcast directly through wireless devices and mobile networks during patients' real-time activities and over limitless distances. However, the transmission of signals through a limited band channel or over multi-propagation suffers from limitations such as inter-symbol interference (ISI). In channel output, the adjacent symbols smudge and integrate with each other by degenerating during error analysis. Equalization filters are used to improve such kinds of deformation. A new adaptive equalization approach is proposed in this paper to extract real broadcasted signals from Gaussian noise-distorted ECG signals using the enhanced meta-heuristic algorithm. The weight optimization strategy of the "adaptive equalization technique" is implemented using oppositional searched coyote optimization algorithm (OS-COA). The main purpose of adapting the improved meta-heuristic-based adaptive equalization technique is to decrease error in the section of receivers, thus ensuring the received ECG signal is error-free. The obtained outcomes are examined to evaluate the performance of error metrics like "mean square error (MSE), and convergence rate" of the introduced model and for comparison with other existing equalization approaches. According to the experimental evaluation, the recommended adaptive linear equalization technique has better extraction performance than other blind and nonlinear equalization approaches.

Keywords: Telecommunication, Inter-Symbol Interference, Adaptive Equalization Technique, Oppositional Searched Coyote Optimization Algorithm, Electrocardiogram Signal Transmission

1. INTRODUCTION

Telecommunication technology is widely used in the telemedicine field to transfer information regarding medicine like therapy, education, and diagnosis [1]. This medical information consists of medical signals, audio signals, video signals, patients' medical records, output data gathered from medical electronic devices (Electroencephalogram (EEG), Electromyography (EMG)), and sound files [2]. ECG is generally used to monitor signals from the heart and diagnosis cardiology functions (i.e., in Intensive Care Units (ICU), where ECG signals are transmitted through ambulatory monitors, ECG records, and telephonic channels [3]. It is necessary to carry out timely treatment and diagnosis of patients with cardiac disease. Hence, it is important to monitor the ECG signals and frequently check the patient's heart activity [4]. The use of wireless communication is rising rapidly, especially in recent years, due to the progression of technologies in radio frequency (RF) systems, digital signal processing, and networks [5]. Due to the rapid growth in wireless communication and the arrival of third-generation (3G) networks, the implementation of ECG in real time is now possible [6].

High-speed mobile channels attain the maximum data transmission rate through the timely transmission of ECG signals [7]. Another limitation is the overlapping of transmitted signals in ISI since the relay of time diffusion in ECG signals causes ECG data error in healthcare receiver stations. In recent years, the need for wireless ECG transmission has increased [8]. However, the instability in wireless channels results in poor service quality in real-time ECG monitoring [9]. ISI is often combined with digital signal transmission. The ISI smudges the pulses, potentially affecting their various symbols [10]. On the other hand, ISI can affect the media transmission cable lines because they have limited band and it allows cellular communications. The presence of noise, channel variation, and limited sources causes ISI [11]. Therefore, it is essential to reduce the ISI attacks and the specification of equalizers to attain reliable digital signal transmission [12].

The interference between channels results from the network phase shift and amplitude but can be reduced by implementing the equalizers [13]. In [14], a new constant modulus algorithm (CMA) is proposed for use as an equalizer. The CMA is described as a blind wireless channel equalizer in various research since it is robust over the destruction of perfect blind equalization (PBE) state [15]. As a result, to minimize the complications in CMA, a fractionally-spaced equalization constant modulus (FSE-CM) algorithm is implemented to develop the

Manuscript received on January 18, 2022; revised on March 23, 2022; accepted on August 24, 2022. This paper was recommended by Associate Editor Kampol Woradit.

The authors are with the Department of Electronics and Communication Engineering, B.S. Abdur Rahman Crescent Institute of Science and Technology, Tamil Nadu, India.

†Corresponding author: vijayalakshmi.b@crescent.education

Digital Object Identifier: 10.37936/ecti-eec.2023211.248608

dithered signed-error constant modulus algorithm (DSE-CMA) [16]. The DSE-CMA is purported to improve the performance of the blind channel equalizer in the macro-cell networks employed in the telemedicine approach. The digital communication system is designed to transmit the signals to ECG and EEG [17]. Hence, an effective framework is required to represent the ECG data and strengthen the broadcasting of ECG signals with wireless channels.

The main objectives of the proposed method are as follows:

- To present a new technique to enhance the transmission of ECG signals with adaptive equalization to acquire real broadcasted signals from the noise-distorted signals obtained through OS-COA.
- To extract the original transmitted ECG signals using the adaptive equalization technique and enhance its performance by adopting a weight optimization strategy using OS-COA with the aim of achieving error-free and noise-free signals.
- To propose an OS-COA algorithm to achieve error-free and noise-amplified ECG signal transmission via the enhanced adaptive equalization technique by optimizing the weight used in the adaptive equalization filter.
- To estimate the efficiency of the recommended method over other conventional works by analyzing the various measures used for demonstrating the effectiveness of the designed model.

The remaining sections of the paper are discussed as follows. Section 2 presents a review of the existing literature. Section 3 denotes the current architectural equalization techniques for ECG signal transmission. Section 4 depicts the adaptive equalization with optimized weight for ECG signal transmission. Section 5 analyzes the enhanced ECG signal transmission using OS-COA. Section 6 presents and discusses the simulation outcomes and Section 7 provides the conclusion.

2. LITERATURE REVIEW

2.1 Related Works

In 2015, Priya *et al.* [18] suggested a mathematical expression to cancel the effect of ISI in ECG transmission signals over wireless networks. The main limitations of signal transmission in digital communication systems are caused by ISI. This paper concentrated on the ISI, in terms of inherent errors caused by overlapping the adjacent symbol present in the signal output. The ECG-transmitted signals were estimated from the output signals with noise using an adaptive equalization technique, and errors in the receiver field minimized by adaptive filters. The results of the proposed method were varied by operational parameters like "mean square Error (MSE), computational complexity, correlation coefficient, and convergence rate." The proposed "adaptive linear equalization" technique demonstrates better results than other equalization approaches.

In 2012, Mahmoud *et al.* [19] proposed the DSE-CMA model for adaptive blind channel equalization. The practicability and performance of EEG and ECG signal transmission was investigated in this work. The adaptive blind channel equalizer for EEG and ECG signal communication was also discussed and compared with other wireless systems like the "global system for mobile communications (GSM) and enhanced data rates for GSM evolution (EDGE)." To obtain the "geometrical-based hyperbolically distributed scatterers (GBHDS)," the channel method for a macro-cell environment was stimulated with angular spreads (AS). The stimulation results in this study showed less complexity and a fast convergence rate. The advantages of this framework make it suitable for telemedicine applications. The output signal of the equalizer is linked to the original transmitted signal in the time-frequency domain.

In 2016, Priya *et al.* [20] discussed the significance of blind equalization for signal transmission over other models like wireless body area networks (WBAN) and 3G mobile networks. This method was compared with other existing equalization methods for "computational complexity, correlation coefficient, convergence rate, and mean square error." The experimental evaluation of the blind equalizer showed similar results to the non-blind equalizer. The equalizers do not depend on learning signals, considered to be one of the advantages of the proposed model. Therefore, this scheme was deemed suitable for implementation in bio-telemetry systems.

In 2011, Lee *et al.* [21] developed real-time data transmission and compression algorithms in e-health terminals for ECG signals. The suggested algorithm included four reconstruction methods and five compressions methods. The efficiency of the proposed algorithm known as downslope trace waveform (DSTW) was estimated, and the algorithm then applied to evaluate the compress ratio (CR) and MIT-BIH arrhythmia database, percent root mean square difference normalized (PRDN), percent root mean square difference (PRD), root quality score (QS) mean square (RMS), and signal-to-noise ratio (SNR). The efficiency of the proposed algorithm was evaluated with other new optimization algorithms. Hence, the algorithm can transmit and compress real-time data, providing optimal results for the bio-signal data transmission model with low bandwidth.

In 2006, Chou *et al.* [22] developed an efficient algorithm for 2D and ECG to compress uneven ECG signals by utilizing intra- and inter-beat correlations. To achieve better correlation, first the ECG signal was converted into 2D images. This process consisted of steps like "QRS detection and alignment, period sorting, and length equalization." The proposed algorithm achieved a "high compression ratio (CR), low percent root mean squared difference (PRD), low maximum error (MAX-ERR), and low standard derivation of errors (STDERR)." The obtained heartbeat signals were rearranged into images for easy compression. The uneven ECG signals were compressed and then combined with another pre-processing 2D method to enhance performance.

In 2015, Priya *et al.* [23] proposed a new method for

***Table 1**: Pros and cons of traditional ECG signal transmission methods.*

Reference	Methodology	Pros	Cons
Priya *et al.* [18]	Adaptive equalization technique	• It performs very well in wireless body area networks. • It obtains superior performance in terms of signal-to-noise ratio and convergence rate.	• At initial iterations, maximum error results, and this issue must be resolved.
Mahmoud *et al.* [19]	DSE-CMA	• This model is suitable for both ECG and EEG wireless transmission. • It is prevalent in realistic environments.	• However, the transmitted ECG signal is harshly distorted in a GBHDS environment.
Priya *et al.* [20]	Blind adaptive equalization	• It reduces computational complexity. • It recovers the transmitted ECG signal in an efficient manner.	• However, it needs training data for processing.
Lee *et al.* [21]	DSTW	• This model performs well even with limited communication resources. • It obtains a high score.	• This model can only be utilized in limited bandwidth communication applications.
Chou *et al.* [22]	Compression algorithm	• It obtains high compression performance. • It reduces the time latency.	• It obtains suboptimal results when the noise is deviated.
Priya *et al.* [23]	LMS	• It achieves better efficiency and simplicity. • It is more suitable for obtaining error-free cardiac signals during monitoring.	• The received signal causes multi-path effects.
Al-Khafaji [24]	LMS	• It efficiently eliminates inter-symbol inference and channel noise.	• Although it obtains optimal results, it suffers from high noise.
Kang [25]	LB-EDF Scheduling algorithm	• It attains low complexity and error. • It is suitable for real-time ECG applications.	• Sometimes, the perceived quality of the reconstructed signal is degraded.

equalizing the transmitted ECG signals and enhancing the performance of the adaptive channel equalizer using the LMS model. Two techniques were adopted: "adaptive white gaussian noise (AWGN)" and Rayleigh fading. The ISI effects were reduced and the equalizers specified to obtain reliable results. The results showed greater accuracy in the bit error rate (BER) over other existing works. Equalizers were used to avoid the transmitted signals intruding on each other; this intrusion was obtained from the phase shift and amplitude of the channel. To overcome these limitations, equalizers were implemented.

In 2016, Al-Khafaji [24] proposed a new method for matching the efficient ECG-transmitted signal with communication channels using an LMS model and enhanced the performance of a "symbol-spaced adaptive channel equalizer." To implement the method AWGN and Rayleigh fading were adopted. The results obtained with this model indicated progressive BER.

In 2020, Kang [25] suggested a scheme to handle the time-varying wireless channels for ECG data transmission and layered coding. In this paper, an adaptive scheme was developed to achieve a higher-quality ECG communication signal in wireless networks. This method consists of a layered coding for ECG data and the "automatic repeat request (ARQ)" based error control technique, merged with "layer-based extended depth of field (LB-EDF)" to provide consistent and scalable monitoring for remote patients. In this process, a set of samples were divided into the base layer allowing adequate information to be available for detecting cardiac disease while various enhancement layers amplified the reconstructed ECG signals. The proposed algorithm improved the efficiency of the reconstructed ECG signals by utilizing an efficient bandwidth.

2.2 Problem Statement

Numerous traditional ECG signal transmission models are reviewed in Table 1. The adaptive equalization technique [18] performs very well in a wireless body area network. It enhances the achievement of the signal-to-noise ratio and convergence rate. On the other hand, at initial iterations, maximum errors exist and this aspect must be resolved. DSE-CMA [19] is suitable for both ECG and EEG wireless transmission prevalent in realistic environments. However, the transmitted ECG signal is harshly distorted in the GBHDS environment.

Blind adaptive equalization [20] reduces computational complexity and recovers the transmitted ECG signal in an efficient manner, though, it needs training data for processing. The DSTW [21] model performs well even with limited communication resources, achieving a high-quality score. This model can only be utilized in limited bandwidth communication applications. The compression algorithm [22] gives better performance and reduces time latency. However, it obtains suboptimal results when the noise is deviated.

LMS [23] provides better efficiency and simplicity, making it more suitable for obtaining error-free cardiac signals during monitoring. Conversely, the received signal causes a multi-path effect. LMS [24] efficiently eliminated the inter-symbol inference and channel noise. Although obtaining optimal results, it suffers from high noise.

The LB-EDF scheduling algorithm [25] attained low complexity and error, making it more suitable for real-time ECG applications. Sometimes, the recognized effect of the reproduced signal is degraded, motivating the researchers to concentrate on suggesting a new equalization algorithm.

3. ADAPTIVE EQUALIZATION TECHNIQUE FOR ECG SIGNAL TRANSMISSION

3.1 Proposed Model and Description

The ECG is used to monitor signals and diagnose cardiac disease [26]. The electric signals are extracted and further monitored by electronic devices. Moreover, the ECG signals are often distorted by multiple sources like noise in the electrode movements, muscle contraction, and interference from other electronic devices. The ECG baseline can be easily attacked by any source, causing the baseline to float and appear noisy. The movement of cables also creates low-frequency noise known as shot noise. These noises can affect the diagnosis of various cardiac conditions. Channel noises are caused by transmitting from one channel to another under weak channel conditions.

The real-life application of ECG data and signal communication over wireless networks are affected by transmission errors in the ECG signal and bandwidth limitations. Wireless channels are often noisier than wired connections and also suffer from shadowing and multi-path fading, affecting the efficiency of reproduced ECG signals. The extraction and removal of noise from the transmitted ECG signal is important for doctors in diagnosing diseases accurately. To overcome the challenges of ECG signal transmission, a new technique is proposed, as shown in Fig. 1.

The purpose of the proposed model is to improve ECG signal transmission in broadband wireless communication. The datasets are gathered from the benchmark ECG heartbeat categorization database. The input ECG heartbeat signals from the dataset are transmitted to ECG formatting $k(a)$ and the formatted ECG signals then passed through a wireless channel $s(a)$. In this wireless channel, Gaussian noise $r(a)$ was added to the transmitted ECG signals. Gaussian noises are often included in digital communication signals. The noise-corrupted ECG signals were subjected to the adaptive equalization technique $v(a)$. During the process, the transmitted original ECG signals are extracted from the corrupted noise signals. These signals are then reformatted $\hat{k}(a)$ and the received signals obtained from the Gaussian noise-corrupted ECG-transmitted signals.

The proposed OS-COA algorithm is implemented to enhance the adaptive equalization technique using the weight optimization strategy. The major purpose of the proposed OS-COA-based adaptive equalization is to decrease the error rate in the obtained signal and to ensure the received ECG signal is error-free.

3.2 ECG Signal for Transmission

ECG signals demonstrate the electrical tasks of the heart. ECG analysis is used to diagnose various cardiac-related diseases. The wirelessly transmitted signals obtained from the ECG aid in the timely diagnosis and appropriate treatment of cardiac disorders. The ECG signals used in this experiment are gathered from the standard ECG database.

3.3 Received Signal

The Gaussian noise $r(a)$ corrupted ECG-transmitted signal is obtained by the receivers as given in Eqs. (1) and (2).

$$b(a) = t(a) + r(a) \tag{1}$$

$$b(a) = s(a) * k(a) + r(a) \tag{2}$$

The received Gaussian noise-corrupted signal is processed by the adaptive equalization technique through the OS-COA algorithm. The ECG signals are transmitted to different band channels, producing fluctuations in the received signals. The transmitted ECG signals are reformatted and received in a similar way to the original transmitted ECG signals. The received ECG signal from the adaptive equalizer contains errors and causes trouble transmission to real-time applications. The meta-heuristic algorithm is implemented to minimize the errors in the received signals, thereby ensuring they are error-free.

4. ADAPTIVE EQUALIZATION WITH OPTIMIZED WEIGHT FOR ECG SIGNAL TRANSMISSION

4.1 Adaptive Equalization Technique

The adaptive equalizer [27] is the converse of a channel filter. The received ECG signals are denoized with the filter instinct reaction. The filter coefficients are upgraded with the weight optimization strategy, whereby the noise-corrupted received signals are extracted from the original signals. If the desired response is observed as $w(a)$, the input vectors $b(a)$ are accessible at each iteration, consequently, the OS-COA algorithm is the right choice for various applications in adaptive signal processing. The flexible linear combiner is activated in two diverse faces of an adaptive system, applied on the basis of the input connections in serial or parallel form. In all cases, the outcome of the combiner is obtained as the denoizing signal $v(a)$ with the linear combination of given input samples. The error signal is calculated as $u(a) = w(a) - v(a)$. The stability and speed of the adaption is regulated by the gain constant (μ). If the error signal is higher, then the proposed OS-COA algorithm uses a unique adaptive liner combiner model. A novel OS-COA

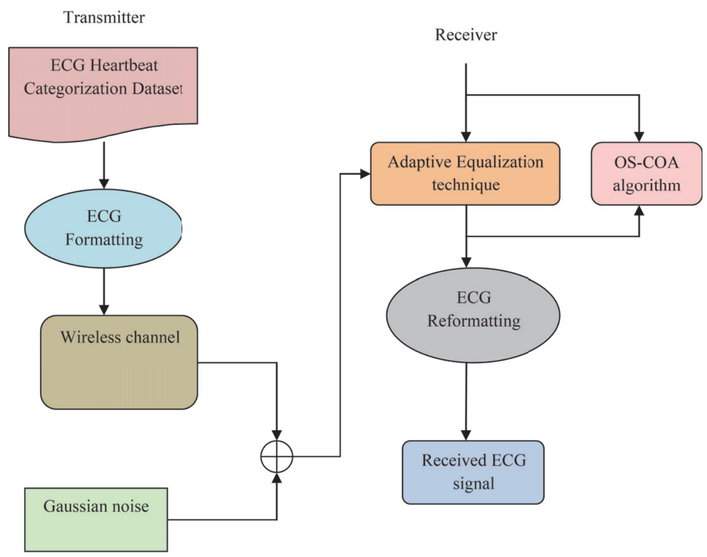

***Fig. 1:** Architectural diagram showing ECG signal transmission with the adaptive equalizer.*

algorithm is implemented to improve the efficiency of adaptive equalization by optimizing the signal weight.

4.2 Weight Optimization Strategy and Algorithmic Steps

The weight optimization [28] strategy is implemented in the adaptive equalization approach to estimate the real broadcasted signals from the noise-distorted ECG signals. The proposed meta-heuristic improved OS-COA algorithm is adopted to enhance the performance of the adaptive equalizer by implementing the weight optimization strategy to obtain more relevant and optimal signals. The weight optimization strategy with the OS-COA algorithm provides a better solution using the adaptive equalization technique. The received ECG signals are error-free and transmitted accurately with the weight optimization strategy. The algorithmic steps are based on the following:

- Step 1: Input the convolved signal $b(a)$ with weight $Wg(a)$.
- Step 2: Determine the deconvolved signal $yb(a) = b(a)^T Wg(a)$.
- Step 3: Calculate the error between the transmitted and received signal.
- Step 4: Update the weight function using the proposed OS-COA.
- Step 5: Determine the filter output using the OS-COA-based updated weight to obtain error-free ECG signals.

5. ENHANCED ECG SIGNAL TRANSMISSION USING THE OPPOSITIONAL SEARCHED COYOTE OPTIMIZATION ALGORITHM

5.1 Conventional COA

The COA [29] algorithm is inspired by the behavior of the Canis latrans species known as Coyote; it is a population-based algorithm and has various algorithm structures. Compared to the Gray Wolf Optimizer (GWO) [30], this algorithm does not depend on social grouping and dominates the rule over animals. The leader of the hunting group is represented as alpha. The population size of the coyotes is split into $R_o \in R^*$ groups over every $R_b \in R^*$. In all groups, coyotes are balanced and equal. Therefore, the population size in the given optimization algorithm is attained with the multiplication of R_o and R_b. The unstable coyotes are rejected for simplification in the initial phase of the given algorithm. Social structure is the main contribution of the COA algorithm and is one of the significant algorithms for solving optimization issues.

The behavior of coyotes is inspired by intrinsic and extrinsic components and forms the basis of social locations in the implementation of a coyote hunting scheme. The variable $\vec{a}$ hunting is represented as the solution variance of global optimization issues. Hence, sco is denoted by social condition, b^{th} as coyote, o^{th} are given as groups in instant time s^{th}, and F is represented as the search gap, denoted in Eq. (3), and also involves the coyote's adaption to the environment $zks_b^{o,s} \in U$.

$$sco_b^{o,s} = \vec{a} = \left(a_1, a_2, \ldots, a_F\right) \tag{3}$$

The initial hunting model of coyotes is used to prepare the entire population. The social constraints are given to every coyote in a random manner. The arbitrary values are allocated in the search space for b^{th} as coyote and o^{th} as pack of n^{th} dimension shown in Eq. (4).

$$sco_b^{o,s} = vy_n + u_n \cdot \left(wy_n - vy_n\right) \tag{4}$$

The variables wy_n and vy_n are denoted as the lower and upper bounds of n^{th} decision variance. u_n is denoted as the real arbitral number in the certain limit of [0,1] in the uniform probability distribution. The adaption of coyotes in the social condition is denoted in Eq. (5).

$$zks_b^{o,s} = z\left(sco_{b^{th}}^{o^{th},s^{th}}\right) \tag{5}$$

Initially, the coyotes are allotted to a group. Moreover, they can be removed and combined into packages or remain individual. The probability of a coyote being rejected from the group is O_E as shown in Eq. (6).

$$O_E = 1.005 \cdot R_b^2 \tag{6}$$

This method is used with the COA algorithm to interconnect with the entire population of coyotes. This group contains two alphas, while the COA takes only one alpha. In the event of minimization, the alpha of o^{th} pack in the instant time s^{th} is shown in Eq. (7).

$$alpha^{o,s} = \left\{ sco_b^{o,s} \middle| arg_{b=\{1,2,\ldots,R_b\}} \min z\left(sco_b^{o,s}\right) \right\} \tag{7}$$

The useful details from the given algorithm are combined and initialized as the actual behavior of the group as shown in Eq. (8).

$$cult_n^{o,s} = \begin{cases} T^{o,s}_{\frac{(R_b+1)}{2},n}, & R_b \text{ odd} \\ T^{o,s}_{\frac{R_b}{2},n} + T^{o,s}_{\frac{(R_b+1)}{2},n}, & \text{otherwise} \end{cases} \tag{8}$$

The variable $T^{o,s}$ is denoted as the social circumstance of the coyote to the o^{th} group in the instant time s^{th} for every n in the limit of $[0,F]$.

The age of the coyote is represented as $age_b^{o,s} \in R$, the birth of a new coyote is represented as the consolidation of two parents' social circumstances in the inspired environment, as shown in Eq. (9).

$$pup_n^{o,s} = \begin{cases} soc_{u1,n}^{o,s}, & urf_n < O_c orn = n_1 \\ soc_{u2,n}^{o,s} & urf_n > O_c + O_x orn = n_2 \\ U_n & \text{otherwise} \end{cases} \tag{9}$$

The variables u_1 and u_2 are denoted as the arbitral coyotes from the o^{th} group, the arbitral dimensions are correspondingly represented as n_1 and n_2 then O_c is represented as the uniform probability distribution, U_n is the random number in the decision term bound of n^{th} dimension and urf_n is shown as the random number in [0,1], created with uniform probability. The culture diversity of coyotes is trained with association and scatter probability. In the beginning phase of COA, O_c and O_x are denoted in Eqs. (10) and (11).

$$O_c = \frac{1}{F} \tag{10}$$

$$O_x = \frac{1 - O_c}{2} \tag{11}$$

The variable O_c is used to represent scatter probability distribution, O_x is denoted as uniform probability. The term F represents the search gap dimension.

Here, the variables ω and γ denote corresponding packs of coyotes in weak conditions. The COA represents coyotes in alpha influence (δ_a) and pack influence (δ_b). The variable bu_1 denotes the random coyote of the groups to the alpha coyote, and bu_2 the random coyote culture compared to the actual behavior of the group. The random coyotes are correspondingly chosen from uniform probability δ_a and δ_b, as depicted here.

$$\delta_1 = cult^{o,s} - sco_{bu_1}^{o,s} \tag{12}$$

$$\delta_2 = cult^{o,s} - sco_{bu_2}^{o,s} \tag{13}$$

Therefore, the novel social circumstance of a coyote is updated using the alpha and park influences as represented in Eq. (14).

$$new\_sco_b^{o,s} = sco_b^{o,s} + u_1\delta_a + u_2\delta_2 \tag{14}$$

The variables u_1 and u_2 are the random numbers at the limit [0,1], shown with uniform probability distribution. The new social circumstance is represented in Eq. (15).

$$new\_fit_b^{o,s} = z\left(new\_sco_b^{o,s}\right) \tag{15}$$

Finally, the coyote's social circumstance is introduced in Eq. (16) and used in global optimization issues.

$$sco_b^{o,s+1} = \begin{cases} new\_sco_b^{o,s}, & new\_fit_b^{o,s} < fit_b^{o,s} \\ sco_b^{o,s}, & \text{otherwise} \end{cases} \tag{16}$$

5.2 Proposed OS-COA

The implemented COA algorithm is applied to more complicated optimization problems since it has the capability to find better quality new solutions and resolves the convergence problem. COA algorithms offer a better solution than PSO and GA as well as reducing the computational time. They enhance the efficiency of operations and resolve both constrained and unconstrained problems. Moreover, the COA algorithm is not efficient for diverse optimization issues. The COA does not fall into the local optimum. Such disadvantages can be solved by introducing a new improved OS-COA algorithm. The birth of the new coyote from random parents in a social condition is implemented in the OS-COA algorithm. To improve the performance of the proposed OS-COA algorithm, $bestfit$ and $worstfit$ are introduced in Eq. (10), as given in Eq. (17).

$$O_c = \frac{1}{F} * \frac{bestfit}{worstfit} \tag{17}$$

As the circumstances are upgraded in terms of the best and worst solutions in OS-COA, the optimal solutions give a higher convergence rate, thus referred to as the

Algorithm 1: Designed OS-COA

```
Initialize the R_o pack and R_b coyote by Eq. (3)
Upgrade the coyote location by Eq. (4)
while number of iteration ≠ maximum
    for each pack o do
        Consider the alpha coyote of the group
        by Eq. (7)
        Initiate the cultural tendency of the pack
        by Eq. (8)
        for every b coyote of the o group do
            Upgrade the social conditions by Eq. (12)
            Estimate the new social solution by Eq. (15)
            Implement new coyotes by Eq. (16)
        end for
        Update the birth and death by Eq. (9)
    end for
    Transform the packs by Eq. (6)
    Upgrade the newborn coyotes by Eq. (18)
    Traditional Update
end while
```

oppositional search algorithm. Furthermore, Eq. (16) is applied to Eq. (11) to update the birth of new coyotes. The modified formula for the proposed OS-COA algorithm is given in Eq. (18).

$$O_x = \frac{1 - \frac{1}{F} * \frac{best\,fit}{worst\,fit}}{2} \tag{18}$$

The proposed OS-COA algorithm can provide high-quality optimal solutions with better stability than other traditional updates. The maximum iteration is 100. The pseudo code for the introduced OS-COA is shown in Algorithm 1. The flowchart for the designed OS-COA algorithm is presented in Fig. 2.

5.3 Objective Model

The main objective of the OS-COA algorithm is to improve the adaptive equalization technique by the weight optimization strategy and minimize the error rate in the received signal. The weight of the signals is optimized using OS-COA and the mean of error is reduced to produce the best optimal solution. The noise signal $b(a)$ is multiplied with the weight function $Wg(a)$ to obtain the original transmitted ECG signal $yb(a)$ given in Eq. (18) and the objective function given in Eq. (19).

$$obj_1 = \underset{Wg(a)}{\arg\min}\,(mean(err)) \tag{19}$$

Here, the term $Wg(a)$ represents the weight used in the optimization strategy, ranging from 0.1–0.9, and err represents an error.

$$err = \sum_{o=1}^{rs} [yy_o - xx_o] \tag{20}$$

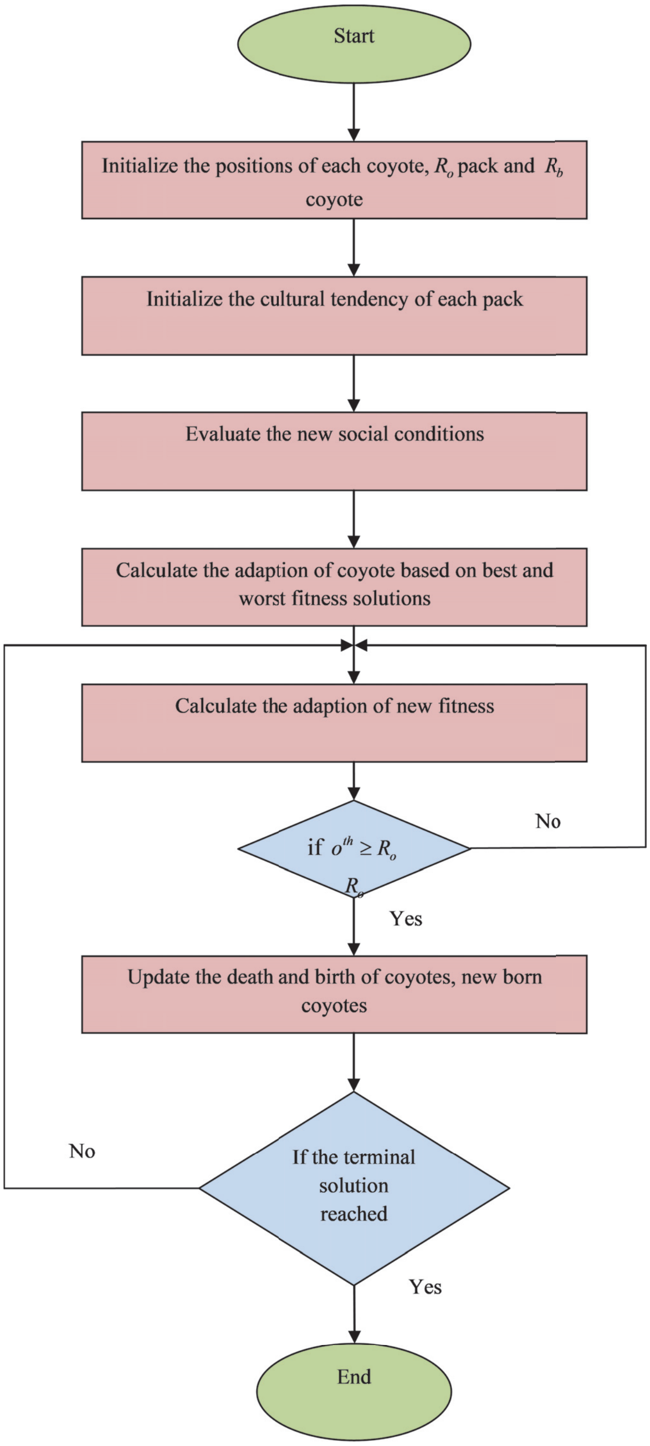

Fig. 2: The flowchart for the designed OS-COA algorithm.

In Eq. (20), the term yy represents the actual signal and xx denotes the received signal with noise. Finally, the transmitted ECG signals obtained are error-free, with no noise interruptions. Thus, it ensures good quality signals are received signals.

5.4 Dataset Description

The benchmark datasets for ECG heartbeat categorization are gathered from https://www.kaggle.com/shayanfazeli/heartbeat (access: Dec. 3, 2021). These datasets contain the heartbeat signals of two heartbeat collections: the PTB Diagnostic ECG Database and the MIT-BIH Arrhythmia Dataset. The two datasets contain large samples for training with DNN. This dataset is used to detect heartbeat classifications using DNN architecture. The heartbeat signals are classified based on the ECG signals for healthy cases and unhealthy cases. The total number of samples taken is 14 552, with a sampling frequency of 125 Hz.

6. RESULTS

6.1 Experimental Analysis

The implemented method for adaptive equalization-based ECG signal transmission in wireless communication networks was executed in MATLAB and the experimental evaluation accomplished. The proposed model was compared with different algorithms and equalization approaches. The performance of the recommended method was evaluated using statistical measures such as worst, standard deviation, best, median, and mean. "The mean is the average value of the best and worst values and the median is referred to as the center point of the best and worst values, whereas the standard deviation is represented as the degree of deviation between each execution." The performance of the proposed method was compared with different meta-heuristic existing algorithms like ROA-AE [31], JA-AE [32], SHO-AE [33], COA-AE [29], HGS-AE, and AO [34] and further compared with AE [18] and SGSM [35].

6.2 Performance Measures

The performance measures utilized in ECG signal transmission models are given here.

(a) L1−Norm "is the sum of the magnitude of vectors in a space. It is the most natural way of measuring the distance between vectors, representing the sum of absolute difference in the components of the vectors" as shown in Eq. (21).

$$\text{L1}-\text{Norm} = ||xx||_1 = \sum_{o=1}^{rs} |xx_o| \tag{21}$$

(b) L2−Norm "is also known as the Euclidean Norm. It is the shortest distance from one point to another" as shown in Eq. (22).

$$\text{L2}-\text{Norm} = ||xx||_2 = \sqrt{\sum_{o=1}^{rs} xx_o^2} \tag{22}$$

(c) L−infinity Norm "is the vector space of essentially bounded measurable functions with the essential supreme norm and only the largest element has any effect" as shown in Eq. (23).

$$\text{L}-\text{infinity Norm} = ||xx||_\infty = \max_{1\le o\le rs} |xx_o| \tag{23}$$

(d) Mean Absolute Error (MAE) "is a measure of errors between paired observations expressing the same phenomenon" as shown in Eq. (24).

$$\text{MAE} = \frac{\sum_{o=1}^{rs} |yy_o - xx_o|}{rs} \tag{24}$$

(e) Mean Absolute Scaled Error (MASE) "is a measure of the accuracy of forecasts. It is the mean absolute error of the forecast values, divided by the mean absolute error of the in-sample one-step naive forecast" as given in Eq. (25).

$$\text{MASE} = \frac{1}{rs} \sum_{o=1}^{rs} u_o \tag{25}$$

(f) Mean Squared Prediction Error (MEP) "measures the expected squared distance between what your predictor predicts for a specific value and what the true value" as shown in Eq. (26).

$$\text{MEP} = \frac{100\%}{rs} \sum_{o=1}^{rs} \frac{yy_o - xx_o}{yy_o} \tag{26}$$

(g) Root Mean Square Error (RMSE) "is one of the most commonly used measures for evaluating the quality of predictions. It shows how far predictions fall from the measured true values using Euclidean distance" as given in Eq. (27).

$$\text{RMSE} = \frac{\sqrt{\sum_{o=1}^{rs} ||yy_o - y\hat{y}_o||^2}}{rs} \tag{27}$$

(h) Symmetric Mean Absolute Percentage Error (SMAPE) "is used to measure the predictive accuracy of models" as shown in Eq. (28).

$$\text{SMAPE} = \frac{1}{rs} \sum_{o=1}^{rs} \frac{|yy_o - xx_o|}{(|yy_o| + |xx_o|)/2} \tag{28}$$

6.3 Performance Analysis on Baseline Algorithms

The performance measures of the implemented model OS-COA algorithm are compared with different optimization algorithms using the various statistical analysis methods shown in Fig. 3. The mean value metrics of the MAE obtained higher values than other existing algorithms, thus the proposed OS-COA-AE algorithm is 53.33% higher than ROA-AE, 56.25% higher than JA-AE, 58.82% higher than SHO-AE, 56.25% higher than COA-AE, 60% higher than HGS-AE and 51.72% higher than AO-AE. The median value measures of the proposed OS-COA-AE algorithm are 50.33% better than ROA-AE,

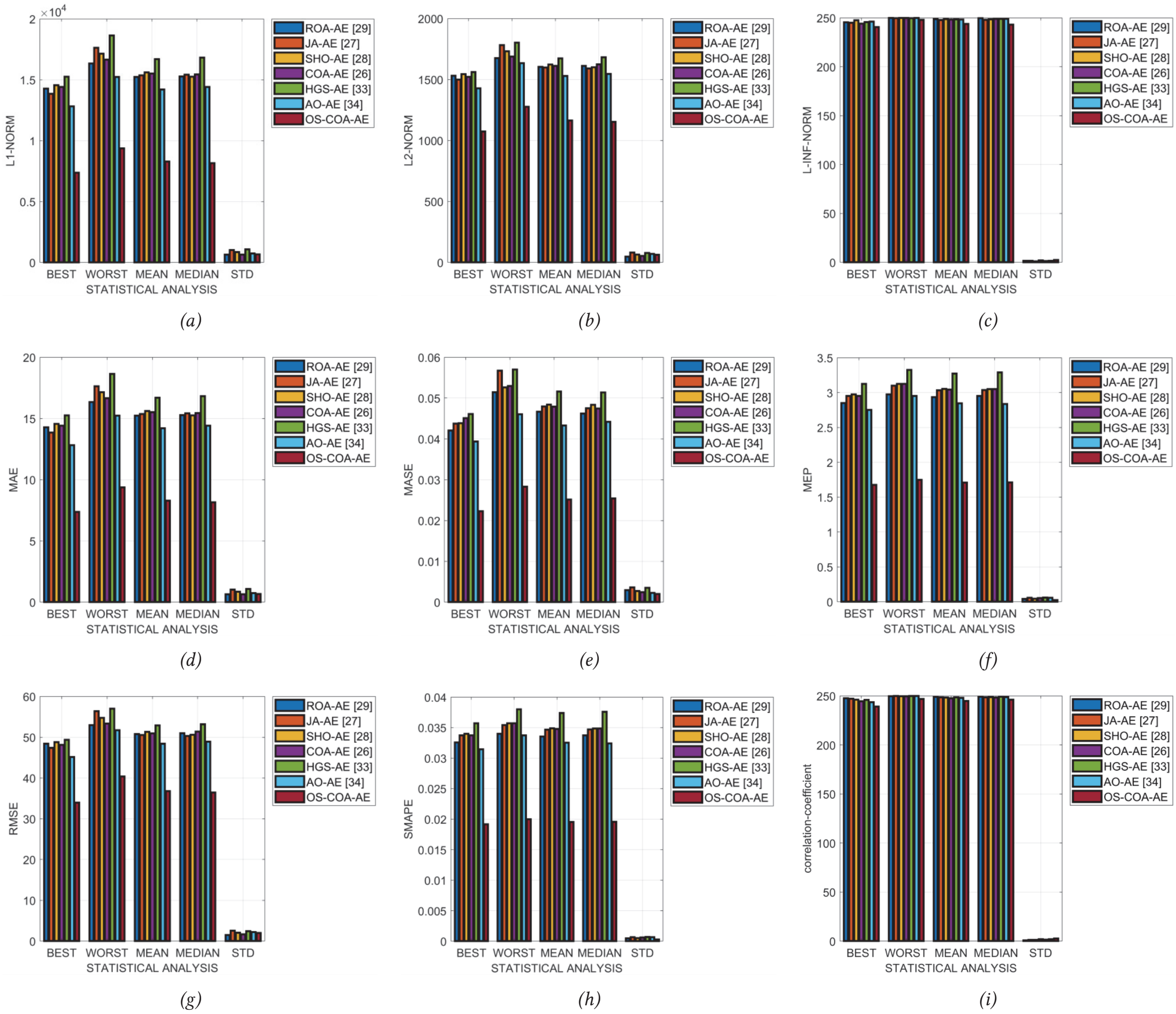

Fig. 3: *Analysis of ECG signal transmission over various heuristic algorithms in terms of (a) L1-Norm, (b) L2-Norm, (c) L-infinity Norm, (d) MAE, (e) MASE, (f) MEP, (g) RMSE, (h) SMAPE, and (i) correlation coefficient.*

50.98% better than JA-AE, 50% better than SHO-AE, 50.33% better than COA-AE, 57.14% better than HGS-AE, and 49.32% better than AO-AE. The efficiency of the implemented algorithm is robust. In each iteration, the error rate is reduced, and therefore, the convergence rate increases. The proposed model reduces the error rate and gives a better performance than other algorithms.

6.4 Performance Analysis on Equalizers

The performance of the ECG signal transmission is optimized by the proposed OS-COA-AE algorithm, and compared with adaptive equalization (AE) and the steepest gradient search method (SGSM) by varying the statistical analysis given in Fig. 4. In considering the L1−Norm, the mean value measures are 33% better than for AE and 50% better than SGSM. At MEP, the median value measures of the proposed OS-COA-AE algorithm are enriched by 44% compared to AE and 46% more superior than SGSM. The overall performance of the implemented OS-COA-AE algorithm obtained more promising results than AE and SGSM.

6.5 Performance Analysis on Convergence

The convergence analysis of the implemented OS-COA algorithm with other heuristic algorithms is given in Fig. 5. In the initial iteration, the cost function values of the proposed OS-COA are 3% higher than COA-AE, 4% higher than SHO-AE, 6% higher than ROA-AE, and 2% higher than JA-AE. At iteration 20, the cost functions of the proposed OS-COA-AE algorithm are 5% better than ROA-AE, 1% better than JA-AE, 4% better than SHO-AE, and 3% better than COA-AE. The cost functions of the proposed algorithm are 1% better than ROA-AE, 1% better than JA, 3% better than SHO-AE, and 5% better than COA at the 97-th iteration. The ROA-AE and SHO-AE algorithms remain stable in all iteration stages. The maximum iterations are taken as 100, with the optimal performance observed by OS-COA-AE. The proposed OS-

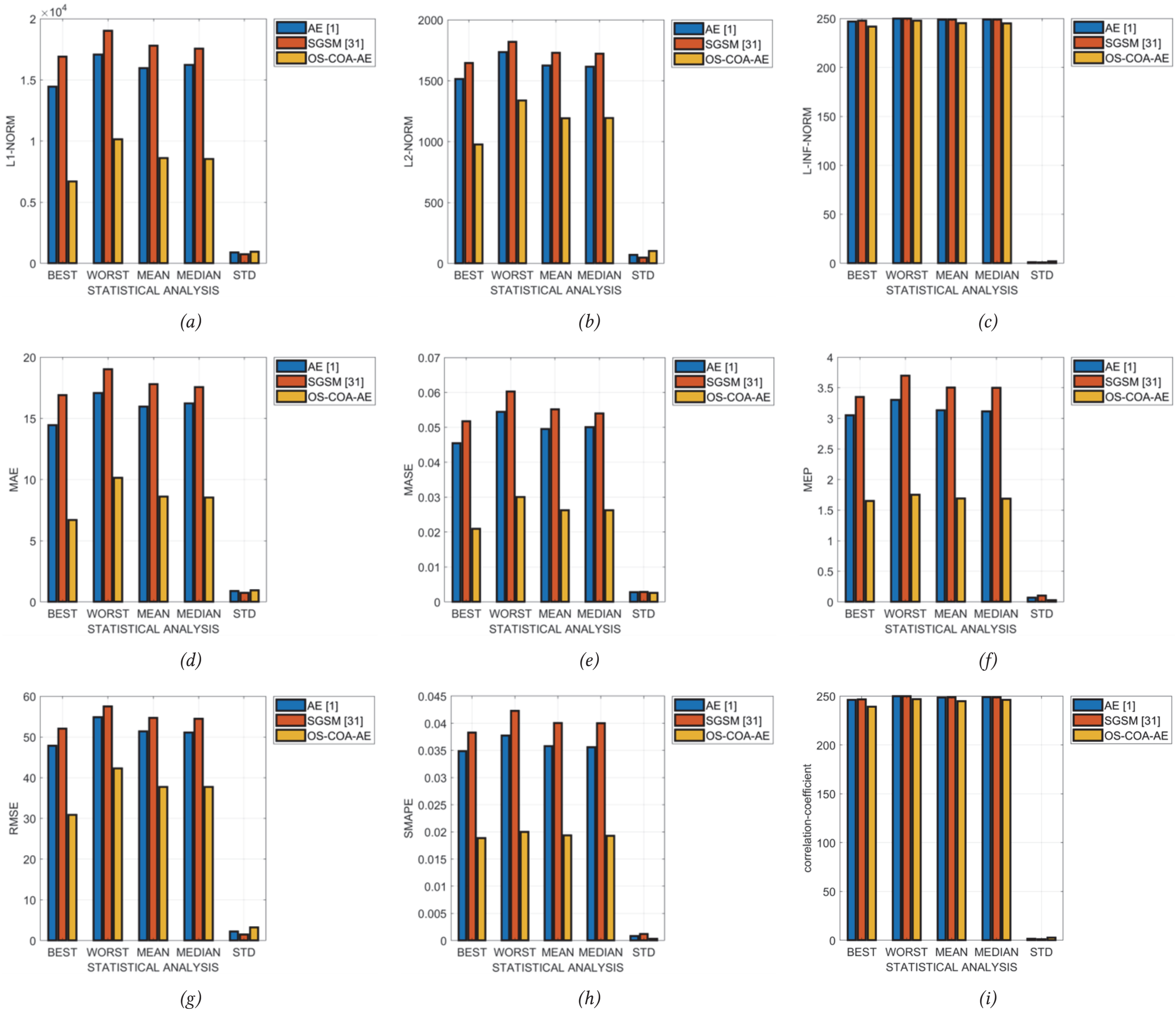

Fig. 4: *Analysis of ECG signal transmission over existing models in terms of (a) L1-Norm, (b) L2-Norm, (c) L-infinity Norm, (d) MAE, (e) MASE, (f) MEP, (g) RMSE, (h) SMAPE, and (i) correlation coefficient.*

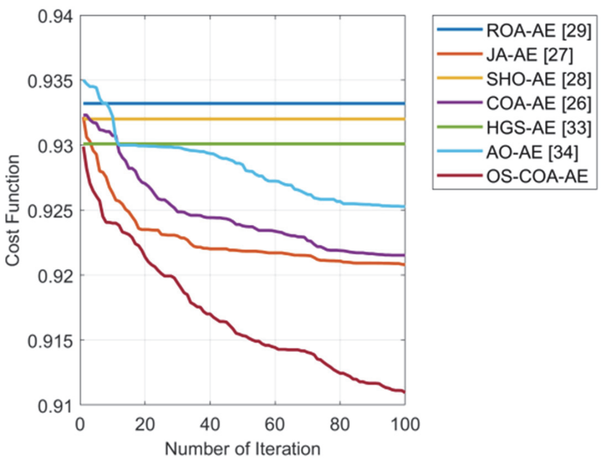

Fig. 5: *Convergence analysis of ECG signal transmission showing a higher convergence rate than other heuristic algorithms.*

COA-AE algorithm obtained a better convergence rate than other heuristic algorithms. Therefore, the mean of error is reduced by adapting the OS-COA-AE algorithm.

6.6 Stimulation Results

The stimulated results for the ECG-transmitted signals using the adaptive equalization technique are given in Fig. 6. As can be observed, clear adaptive equalized output is obtained for the transmitted ECG signals. Initially, the input signal is taken from the standard benchmark datasets. Furthermore, the input signal emits noises from the ECG-transmitted signal. Finally, with the help of the adaptive equalized techniques, noise is removed from the signals and adaptive equalized outcomes obtained. Hence, the findings reveal that performance is enhanced in the suggested model.

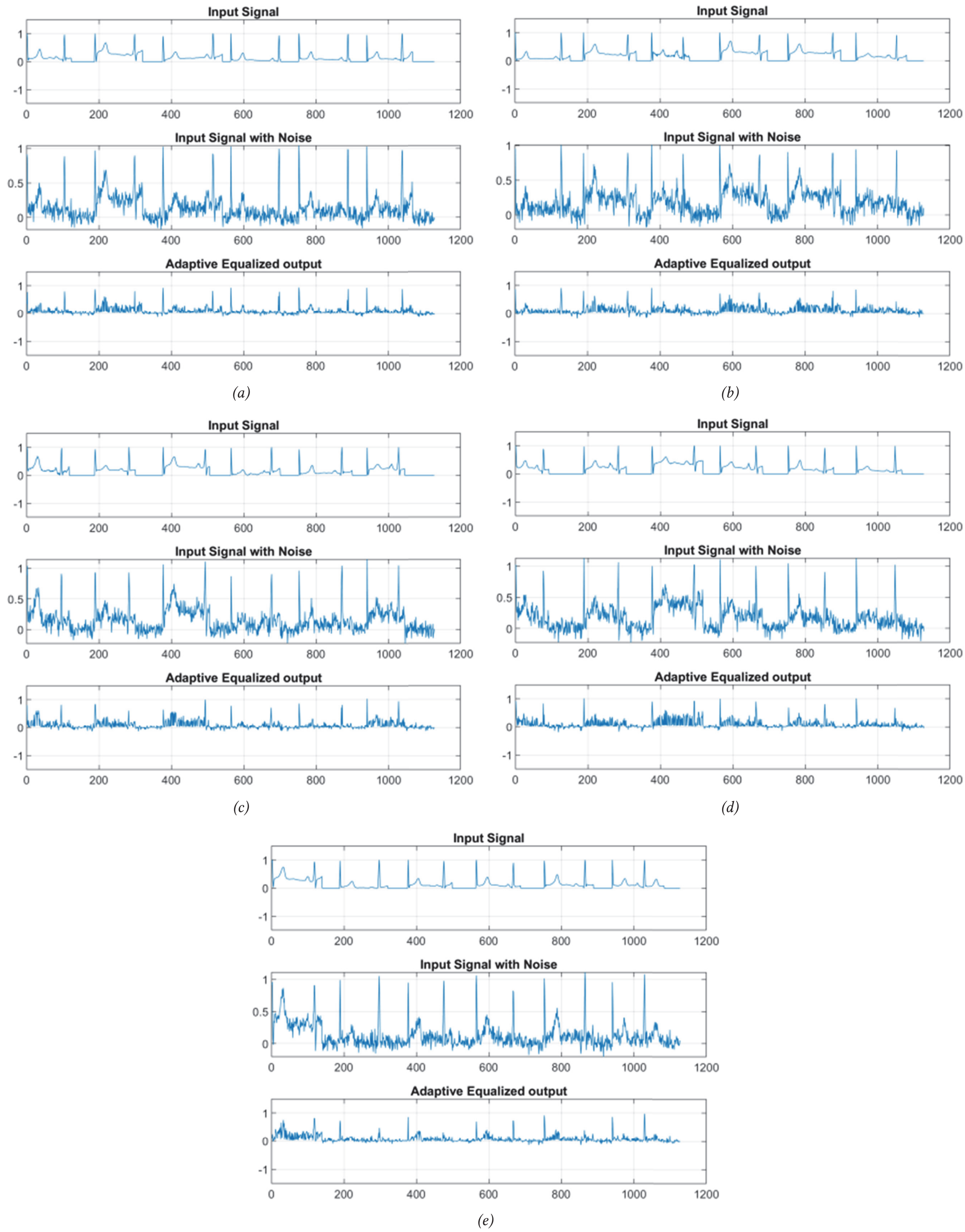

***Fig. 6**: Stimulation analysis of ECG-transmitted signals (a) sample signal 1, (b) sample signal 2, (c) sample signal 3, (d) sample signal 4, and (e) sample signal 5.*

6.7 Overall Performance Analysis

The overall performance of the proposed ECG signal transmission model is established with the OS-COA-AE algorithm and adaptive equalization technique. Here, the proposed OS-COA-AE algorithm is compared with ROA-AE, JA-AE, SHO-AE, and COA-AE. The OS-COA-

***Table 2**: Overall performance analysis of ECG signal transmission compared with other heuristic algorithms.*

Algorithms	BEST	WORST	MEAN	MEDIAN	STD
ROA-AE [29]	0.93222	0.93222	0.93222	0.93222	1.23×10^{-15}
JA-AE [32]	0.92082	0.93217	0.92275	0.92185	0.002401
SHO-AE [33]	0.93202	0.93202	0.93202	0.93202	5.58×10^{-16}
COA-AE [29]	0.92154	0.93232	0.92466	0.92378	0.003068
HGS [36]	0.93011	0.93011	0.93011	0.93011	4.46×10^{-16}
AO [34]	0.92029	0.93002	0.92332	0.92328	0.00256
OS-COA-AE	0.91098	0.9299	0.91685	0.91533	0.00468

AE algorithm achieves better results as illustrated in Table 2. The comparison of the OS-COA algorithm with ROA-AE, JA-AE, SHO-OS-COA-AE, and COA-AE shows promising results. The mean value measures of the OS-COA-AE algorithm are 1.67% higher than ROA-AE, 2% higher than JA-AE, 1.65% higher than SHO-AE, 1% higher than COA-AE, 1.74% higher than HGS-AE, and 4% higher than AO-AE. Therefore, the proposed OS-COA-AE algorithm obtains better results than other heuristic algorithms when all measures are evaluated.

6.8 Time Analysis Computation

The time analysis computation for the proposed ECG signal transmission model is evaluated with the OS-COA-AE algorithm and optimization algorithms as shown in Table 3. As can be observed, the proposed OS-COA-AE model attains 87.02%, 21.83%, 79.95%, and 1.23% minimization compared to ROA, JA, SHO, and COA, respectively. Hence, the proposed OS-COA-AE algorithm is proven to provide better minimum results than other heuristic algorithms.

7. CONCLUSION

In this work, the challenges of ECG signal transmission in wireless communication networks are considered. ECG signal transmission has limitations such as noise corruption, electrode movement, and so on. To overcome these limitations and improve ECG signal transmission, a new adaptive equalization technique using the OS-COA algorithm is implemented. The ECG-transmitted signals are corrupted with Gaussian noise. To obtain an original transmitted signal from noise-corrupted signals, the proposed model uses the adaptive equalization technique with the weight optimization strategy to enhance performance. Finally, the performance of the adaptive equalization technique is enhanced with the OS-COA algorithm. The performance analysis of OS-COA-AE algorithm with other heuristic algorithms shows that it is 5% more superior than ROA-AE, 1% more superior than JA-AE, 3% more superior than SHO-AE, and 5% more superior than COA-AE in terms of mean value. The performance of the proposed OS-COA-AE algorithm with the adaptive equalization technique provides error-free signals. In the future, this technique can be performed in real-time applications by adopting various equalization techniques. In the future, the recommended model will be expanded to include intelligent and hybrid techniques to address noise in the contract group.

***Table 3**: Time analysis computation of ECG signal transmission compared with other optimization algorithms.*

Algorithms	ROA [29]	JA [32]	SHO [33]	COA [29]	OS-COA-AE
Time (s)	58.817	9.7655	38.084	7.7286	7.6332

REFERENCES

[1] C.-T. Lin *et al.*, "An intelligent telecardiology system using a wearable and wireless ECG to detect atrial fibrillation," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 3, pp. 726–733, May 2010.

[2] K. Hung and Y.-T. Zhang, "Implementation of a WAP-based telemedicine system for patient monitoring," *IEEE Transactions on Information Technology in Biomedicine*, vol. 7, no. 2, pp. 101–107, Jun. 2003.

[3] B. Kim, S. Yoo, and M. Lee, "Wavelet-based low-delay ECG compression algorithm for continuous ECG transmission," *IEEE Transactions on Information Technology in Biomedicine*, vol. 10, no. 1, pp. 77–83, Jan. 2006.

[4] G. Xu, "IoT-assisted ECG monitoring framework with secure data transmission for health care applications," *IEEE Access*, vol. 8, pp. 74 586–74 594, 2020.

[5] T. Ma, P. L. Shrestha, M. Hempel, D. Peng, H. Sharif, and H.-H. Chen, "Assurance of energy efficiency and data security for ECG transmission in BASNs," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 4, pp. 1041–1048, Apr. 2012.

[6] A. Hernandez, F. Mora, M. Villegas, G. Passariello, and G. Carrault, "Real-time ECG transmission via internet for nonclinical applications," *IEEE Transactions on Information Technology in Biomedicine*, vol. 5, no. 3, pp. 253–257, Sep. 2001.

[7] Y. Cho, H. Shin, and K. Kang, "Scalable coding and prioritized transmission of ECG for low-latency cardiac monitoring over cellular M2M networks," *IEEE Access*, vol. 6, pp. 8189–8200, 2018.

[8] N. F. Güler and U. Fidan, "Wireless transmission of ECG signal," *Journal of Medical Systems*, vol. 30, no. 3, pp. 231–235, Jun. 2006.

[9] H. Xu and K. Hua, "Secured ECG signal transmission for human emotional stress classification in wireless body area networks," *EURASIP Journal on Information Security*, vol. 2016, 2016, Art. no. 5.

[10] F. Sufi and I. Khalil, "A new feature detection mechanism and its application in secured ECG transmission with noise masking," *Journal of Medical Systems*, vol. 33, no. 2, pp. 121–132, Apr. 2009.

[11] G.-Y. Cho, S.-J. Lee, and T.-R. Lee, "An opti-

mized compression algorithm for real-time ECG data transmission in wireless network of medical information systems," *Journal of Medical Systems*, vol. 39, 2015, Art. no. 161.

[12] M. Liu, H. Hao, P. Xiong, F. Lin, Z. Hou, and X. Liu, "Constructing a guided filter by exploiting the butterworth filter for ECG signal enhancement," *Journal of Medical and Biological Engineering*, vol. 38, no. 6, pp. 980–992, Dec. 2018.

[13] M. Rupp, "Convergence properties of adaptive equalizer algorithms," *IEEE Transactions on Signal Processing*, vol. 59, no. 6, pp. 2562–2574, Jun. 2011.

[14] D. Godard, "Self-recovering equalization and carrier tracking in two-dimensional data communication systems," *IEEE Transactions on Communications*, vol. 28, no. 11, pp. 1867–1875, Nov. 1980.

[15] R. Johnson, P. Schniter, T. Endres, J. Behm, D. Brown, and R. Casas, "Blind equalization using the constant modulus criterion: a review," *Proceedings of the IEEE*, vol. 86, no. 10, pp. 1927–1950, Oct. 1998.

[16] J. Jusak and Z. Hussain, "Evaluation of a sinusoidally-distributed dithering for signed-error constant modulus algorithm: performance comparison with uniformly-distributed dithering," in *Workshop on the Internet, Telecommunications and Signal Processing (WITSP)*, Adelaide, Australia, 2004.

[17] S. Abrar, A. Zerguine, and M. Deriche, "Soft constraint satisfaction multimodulus blind equalization algorithms," *IEEE Signal Processing Letters*, vol. 12, no. 9, pp. 637–640, Sep. 2005.

[18] L. Priya, A. Kandaswamy, R. P. Ajeesh, and V. Vignesh, "Adaptive equalization algorithm for electrocardiogram signal transmission," in *Advances in Intelligent Systems and Computing*, M. Senthilkumar, V. Ramasamy, S. Sheen, C. Veeramani, A. Bonato, and L. Batten, Eds. Singapore: Springer, 2015, pp. 217–226.

[19] S. S. Mahmoud, Q. Fang, Z. M. Hussain, and I. Cosic, "A blind equalization algorithm for biological signals transmission," *Digital Signal Processing*, vol. 22, no. 1, pp. 114–123, Jan. 2012.

[20] L. Priya, A. Kandaswamy, and C. D. Lakshmi, "Blind signal processing for electrocardiogram signal transmission," *Journal of Scientific & Industrial Research*, vol. 75, pp. 547–551, Sep. 2016.

[21] S. Lee, J. Kim, and M. Lee, "A real-time ECG data compression and transmission algorithm for an e-health device," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 9, pp. 2448–2455, Sep. 2011.

[22] H.-H. Chou, Y.-J. Chen, Y.-C. Shiau, and T.-S. Kuo, "An effective and efficient compression algorithm for ECG signals with irregular periods," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 6, pp. 1198–1205, Jun. 2006.

[23] L. Priya, A. Kandaswamy, V. Danvanth, N. Chezhiyan, and J. Hariram, "Performance evaluation of equalization algorithms for electrocardiogram signal transmission," *International Journal of Computer Science and Information Technologies*, vol. 6, no. 6, pp. 5184–5188, 2015.

[24] Y. S. A. Al-Khafaji, "New approach of equalizing electrocardiographic signals using least mean squares technique," *International Journal of Science and Research*, vol. 7, no. 1, pp. 620–623, Jan. 2018.

[25] K. Kang, "An adaptive framework for real-time ECG transmission in mobile environments," *The Scientific World Journal*, vol. 2014, 2014, Art. no. 678309.

[26] G. R. Bojja, M. Ofori, J. Liu, and L. S. Ambati, "Early public outlook on the coronavirus disease (COVID-19): A social media study," *AMCIS 2020 Proceedings*, 2020.

[27] G. Malik and A. S. Sappal, "Adaptive equalization algorithms: An overview," *International Journal of Advanced Computer Science and Applications*, vol. 2, no. 3, pp. 62–67, Mar. 2011.

[28] A. S. Prakaash and K. Sivakumar, "Optimized recurrent neural network with fuzzy classifier for data prediction using hybrid optimization algorithm: Scope towards diverse applications," *International Journal of Wavelets, Multiresolution and Information Processing*, vol. 19, no. 02, 2021, Art. no. 2050074.

[29] Z. Yuan, W. Wang, H. Wang, and A. Yildizbasi, "Developed coyote optimization algorithm and its application to optimal parameters estimation of PEMFC model," *Energy Reports*, vol. 6, pp. 1106–1117, Nov. 2020.

[30] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in Engineering Software*, vol. 69, pp. 46–61, Mar. 2014.

[31] A. R. Moazzeni and E. Khamehchi, "Rain optimization algorithm (ROA): A new metaheuristic method for drilling optimization solutions," *Journal of Petroleum Science and Engineering*, vol. 195, Dec. 2020, Art. no. 107512.

[32] R. V. Rao, "Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems," *International Journal of Industrial Engineering Computations*, vol. 7, pp. 19–34, 2016.

[33] G. Dhiman and V. Kumar, "Spotted hyena optimizer: A novel bio-inspired based metaheuristic technique for engineering applications," *Advances in Engineering Software*, vol. 114, pp. 48–70, Dec. 2017.

[34] L. Abualigah, D. Yousri, M. A. Elaziz, A. A. Ewees, M. A. Al-qaness, and A. H. Gandomi, "Aquila optimizer: A novel meta-heuristic optimization algorithm," *Computers & Industrial Engineering*, vol. 157, Jul. 2021, Art. no. 107250.

[35] S. Chatterjee, R. S. Thakur, R. N. Yadav, L. Gupta, and D. K. Raghuvanshi, "Review of noise removal techniques in ECG signals," *IET Signal Processing*, vol. 14, no. 9, pp. 569–590, Dec. 2020.

[36] Y. Yang, H. Chen, A. A. Heidari, and A. H. Gandomi, "Hunger games search: Visions, conception, implementation, deep analysis, perspectives, and towards performance shifts," *Expert Systems with Applications*, vol. 177, Sep. 2021, Art. no. 114864.

R. Iniyavan received the B.E. degree in Electronics and Communication Engineering from Anna University, Tamil Nadu, India in 2006. He received the M.Tech degree in Communication Engineering from the VIT University, Tamil Nadu, India in 2008. He is currently pursuing Ph.D. Degree with B.S. Abdur Rahman Crescent Institute of Science and Technology, Chennai, Tamil Nadu, India.

B. Vijayalakshmi received her Master's degree in Optical Communication Engineering from Anna University, Chennai, India. She carried out her research work in 3D scene generation using two 2D images through sponsored project. Since 2003, she has been a faculty in Electronics and Communication Engineering Department of different engineering colleges at Tamil Nadu. During her tenure, for more than four years she handled the capacity of the Principal in an engineering college, affiliated by the "Anna University" and approved by the AICTE. Currently, she is serving as a professor in Electronics and Communication Engineering Department at B.S. Abdur Rahman Crescent Institute of Science and Technology, Chennai, India. Currently she is taking care of collaborative international research with Purdue University under SERB–DST–OVDF programme. More than 32 papers were published in various peer reviewed international journals, national journals and at conferences. Her current research interests include image processing, noise removal in VLC, optical communication, perceptual image analysis, 3D scene generation and antenna design. She is a Life member in IETE, CSI and STTA.