Optimization of Spreading Code Using Modified Differential Evolution for Wireless Communication

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Abstract
Spread spectrum linked to optimization techniques play a very important role in today’s world. Optimization gives the best one among all the solutions and the spread spectrum is used to minimize distortion, hence optimized spreading code is very important in wireless communication. This study shows a comparison of two recent modified techniques of differential evolution (DE) with the help of engineering design problems and application of that modified DE, considering the better one, in wireless communication to optimize logistic map based spreading code. A comparative study of properties of both optimized and non-optimized spreading code is also discussed in this paper. The performance of the optimized spreading code is also evaluated with the help of bit error rate (BER) by applying it in static and dynamic direct sequence spread spectrum system (DSSS). The performance of the proposed technique (optimized dynamic logistic map code based DSSS) displays better results than non-optimized spreading code and orthogonal spreading code considering BER. Static optimization is improved by 40% than non-optimized static, dynamic optimization is improved by 70% than static optimization but orthogonal is showing 33% improvement comparing to static optimization and dynamic optimization is improved by 56% than orthogonal one. Therefore, the proposed method can be efficiently applied in the wireless communication system.

Keywords Spreading code · Differential evolution · Optimization · Wireless communication · Logistic map · Wavelet transform

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1 Introduction

The meaning of the spread spectrum in wireless communication means signal bandwidth expansion by multiplying the message signal with another signal called spreading signal (Pseudo Noise (PN) sequence). Starting from the military applications, in the current and also in the next generation of wireless communication techniques, spread spectrum plays a vital role [1, 2]. Using chaotic code (Logistic map code) in spread spectrum communication shows powerful properties like interference mitigation, robustness against interference and noise, low probability of intercept, less BER, CDMA (code division multiple access) [3] realization etc. over the conventional methods like Gold code, PN code, Kasami code, Walsh code, etc. Not only that, the results can be enhanced by applying optimization in chaotic code. Optimization is a very important topic because it helps to find the best solution from the number of solutions. The problems of Real world optimization are characterized as either constrained optimization problems or unconstrained optimization problems [4]. The constrained optimization problems plays an important role in engineering design issues however they may cause the search process difficult. If the exploration and exploitation are properly addresses then they may lead to the improved performance of a search algorithm. The exploration refers to a process in which there is a visit to the new regions for search space and during exploitation, the neighborhood of previously visited points are being visited and that too by means of maintaining a very good ratio among the exploration and the exploitation to achieve a fruitful result [5]. There are several researchers who have proposed various approaches and that too by examining the solution of the specific real world engineering problems [6]. Since these realistic problems are basically nonlinear and complex in nature therefore the classical optimization methods are unable to achieve a global optimum. Hence, over the years the application of metaheuristic approaches to address such problems has become very important [7], e.g. genetic algorithm (GA), ant colony optimization (ACO) algorithm particle swarm optimization (PSO) algorithm, simulated annealing (SA) algorithm are used [8, 9]. Apart from these algorithms, the framework of differential evolution (DE) with enhanced parameters can also play a vital role to resolve the realistic optimization issues in engineering applications. In the year 1995, use of complicated computing method of differential evolution (DE) algorithm was recommended by Price and Storm. Hence optimized chaotic code plays a very important role in wireless communication techniques [10, 11]. Considering optimization, DE is an important evolutionary technique, enhances its parameters such as, initialization of population, mutation, crossover, etc. to resolve realistic optimization issues also in wireless communication [12, 13]. To solve global optimization issues, DE plays a very important role, which is a well-known evolutionary algorithm based on population and it is proposed [14]. To modify DE exponential scale factor and wavelet transform is used because in DE, using scaling factor (F) and crossover rate (CR), exploration and exploitation are balanced. For greater value of F and CR, in the search area, there is a high probability to skip the true solution. To overcome this drawback, the scale factor is replaced by an exponential scale factor and to increase the performance of local search and decrease the significance of mutation wavelet based DE is used and to increase the performance of local search and decrease the significance of mutation wavelet based DE is used.

Considering background, In today’s world, the spectrum will be a scarce commodity; its utilization shall be of utmost importance. Hence spread spectrum linked to optimization techniques plays a vital role in today’s world [15]. Works of literature make it clear that PN and Gold codes are limited to fixed sequence lengths with a system configuration.
Also, flexibility is less because we cannot generate multiple numbers of sequences for the same sequence length. Usually, to generate the PN sequence, certain sum-store blocks and LFSR (linear feedback shift register) are used. Also, to generate Gold code LFSR is used because the generation of Gold code is done by exclusive-OR of two PN sequences, hence for both PN and Gold code, a physical structure is needed which consumes more power with less flexibility [1, 16–18]. There are deviations in the propagation medium in fading conditions. In that case, a flexible spreading code is more suitable than a fixed length one. A logistic map based signal is the sensitive dependence on the initial condition and these properties have increased the interest in using chaos in many fields of Science and Telecommunications [19]. Chaos codes are dynamically formulated combinations that have been established to be useful for a host of scenarios in wireless communication. The generation of chaotic code is very simple. Even for very long sequences only a few functions and parameters are needed. In addition, a huge number of diverse sequences can be generated just by changing its initial condition. Chaotic sequences are reproducible, correlated and dynamic, which can be very helpful in enhancing the security of transmission in communication. Again optimization is a technique by which we can find the best solution among all the solutions. Here, differential evolutionary algorithm is used as a stochastic algorithm [20, 21]. Stochastic algorithms are generally nature-inspired algorithms, they have flexible behavior to adapt to a changing environment [7]. Therefore, the primary focus of the work is to explore the possibility of improved performance that may be derived using modified Differential Evolution. Further, the deployment of modified DE in a chaotic system applying in wireless communication and other engineering applications like gas transmission compressor design, optimal capacity of gas transmission capacity and design of gear train etc. To optimize chaos code Differential Evolutionary Algorithm can be considered because it has random search nature, fewer parameter setting, valid for high dimensional complex problems and have high performances. Also, hybridization of stochastic algorithm is important to improve the Convergence Speed, to balance the Exploration (diversification) and Exploitation (intensification) process, to avoid trapping in local optima and to improve the quality of the solutions. Hence, the work explores the spin-offs that are likely to be obtained from optimized link oriented chaos system supported wireless techniques.

Literature reflects that DE shows high-quality performance in application with different optimization problems [22]. Also various enhance methods of DE by modifying its parameters show a very good performance comparing to different recent optimization techniques [23].

This paper shows a comparative study of two recent modified techniques of DE with the help of engineering design problems and application of that modified DE (considering the better one) in wireless communication to optimize logistic map based spreading code. In a comparative study of DE, modification of DE is done with the help of wavelet transform [23] and exponential scale factor. A comparative study of properties of both optimized and non-optimized spreading code is also discussed in this paper. The performance of the optimized spreading code is also evaluated with the help of BER by applying it in static and dynamic DSSS system. The performance of the proposed technique (optimized logistic map code based DSSS) displays better results considering BER. Hence the proposed method can be efficiently applied in the wireless communication system.

The paper is prearranged as shown in the following; the literature review is discussed in Sect. 2. The proposed method is explicated in Sect. 3. Parameter settings and experimental outcomes are illustrated in Sect. 4. Section 5 presents the conclusion and references are in Sect. 6.
2 Literature Review

The modification of the initialization of population along with the mutation rate is done in [23] using logistic map and wavelet transformation in DE respectively which increases the convergence rate and accordingly, after which test is done on various benchmarks problems. Thereafter, the results are compared with the state of the art algorithms along with different real-time none linear engineering problems to obtain their performance.

An inflationary differential evolution based on multi-population adaption is proposed in [13] which combines the local search mechanisms of monotonic basin hopping with the basic differential evolution as a result of which the differential evolution parameters namely CR and F get automatically adapted with the size of the local restart bubble as well as the number of local restarts of monotonic basin hopping. The aforesaid algorithm a simple as well as effective mechanism to avoid multiple detections of the same local minima and it allows the algorithm to decide as to whether to start a local research. The algorithm has been tested over more than 50 test functions.

A comparison is made by in [12] between the performance of others spreading code in terms of Bit Error Rate, Cross co-relation and average interference which is presented by comparing the generation of optimum chaotic spreading codes by using genetic algorithm.

The derivation of generation of binary sequence from chaotic sequences over $\mathbb{Z}_4$ is proposed in [10] and the six chaotic situation which are considered in [10] are Tent Map, Logistic map, Quadratic Map, Cubic Map, and Bernoulli Map and using this equations generation of sequence over $\mathbb{Z}_4$ is obtained and the same are converted by using polynomial mapping to binary sequence. Moreover, for cross co-relation and linear-complexity properties, the segments of sequences of different lengths are tested and accordingly it is found that some segments of different lengths have got good co-relations and linear-complexity properties. As compared to the Gold sequences and Kasami sequences, the BER performance in the DS-CDMA (Direct Sequence Code Division Multiple Access) communications system is found to be better by using this binary sequences.

This article presentation is made on a design of a dynamic chaotic spreading sequence to apply them in a DSSS based system along with the considerations of wireless channels (Rayleigh and Rician) in [1]. Moreover, a presentation is made after a comparison of a linear and none linear channels with static chaotic sequence in term of a bit error rate, computational time, mutual information and signal power for faded channel, evaluations of performance is done taking into consideration of different modulation schemes, which finally dictates the efficiency of generated code. A comparison of the performance of the generated dynamic logistic map-based sequence is done to that of what is obtained from the gold code under equivalent conditions.

Presentation of the detailed history, characteristics strengths, variants and weaknesses of DE are made in [11]. Identification of seven broad areas are made as different domains of application of DE in wireless communications it was observed that the two major areas where the DE is applied are the coverage area maximization and energy consumption minimization. Quality of service, updating mechanism are the other areas where candidate positions learn from a large diversified search region, security and related filed applications.

The implementation of ultra-wideband (UWB) communication systems with eight transmitting and receiving ring in antenna arrays are done in [20], to test the bit error rate and capacity performance. Calculation of the impulse response of the system is done by using the ray-tracing technique to compute any given indoor wireless environment. To find the excitation current and also to feed the line length of each antenna to form the
appropriate beam pattern which can reduce the bit error rate and which can increase the channel capacity and receiving energy. It is seen by C. Chiu that in both of sight and non-line, the SADDE (Self Adaptive Dynamic Differential Evolution) had better results.

Author tested the capacity performance and bit error rate by implementing eight transmitting and receiving antenna arrays in communication system based on ultra wide band in [20]. The system (indoor wireless environment) impulse response can be evaluated by utilizing ray-tracing technique. The problem with multiobjective optimization are formed by reforming problem with synthesized beamforming. Particle swarm optimization (PSO) and SADDE are utilized to find the feed line length and excitation current of each antenna to generate proper beam pattern. This newly generated pattern can increase the receiving energy and channel capacity and can reduce the bit error rate. Results display that convergence speed of SADDE is better than PSO. Not only that in case of non line of sight and line of sight cases also SADDE is more efficient than PSO.

Authors of the paper [11] explains the literature review of differential evolution and also application in the field of wireless communication. Strengths, characteristics, variants, weaknesses etc., all the detailed history are explained by the authors. Differential Evolution with seven different domain of applications in the field of wireless communication are identified in this paper. Minimization of energy consumption and maximization of coverage area are the two major filed in this paper where differential evolution is applied. Not only that other areas are like quality of service, security, updating mechanism and various related field of applications. Problems deal with wireless communications are generally multiobjective optimization which can be handled by hybrid DE.

In this paper [24] MDE-WOA (hybrid whale optimization algorithm) is presented by the authors. Here addition of modified DE operator having capacity of strong exploration to improve local optimum avoidance with WOA having lifespan mechanism is executed. To enhance the accuracy and to increase the convergence speed an asynchronous model is utilized. 13 benchmark functions along with 3 engineering problems are used to test the proposed MDE-WOA technique. Considering robustness and accuracy MDE-WOA shows better results than others.

Authors of the paper [25] proposed IDE (improved version of DE) for ORPD (optimal reactive power dispatch) problem and also for benchmark functions. Here, objective function of ORPD is total active power loss minimization. Constraints are like transformers tapping, generators, other reactive power source, shunt reactors. To determine the control variable’s best vector to minimize power loss under considering the constraints. The proposed system improved the convergence speed along with diversity and quality are also maintained.

In this study [26] a new hybrid technique is used in which Marine Predators Algorithm and Binary Differential evolution are two metaheuristics algorithms are utilized to solve automatic clustering problems. Eight multi omics sets of data from TCGA (The Cancer Genome Atlas) are used for performance verification also 4 recently developed metaheuristic algorithms are utilized. Results displays that modified technique is not only the fastest one but also outperformed the competitors.

To generate adversarial perturbations, differential evolution is used in this paper by the authors in CNN (convolutional neural network). Effectiveness of various types of DEs are evaluated in this paper [27].

In this study [28], to regulate the frequency of power electric system a method is proposed known as hDE-PS (hybrid differential evolution and pattern search). For analysis and design purpose FOPID (Fractional-order proportional integral derivative) controller is applied. The area where control method is applied are 2 area thermal system and 2 area
diverse source power system having and without having HVDC (high voltage direct current) linkage. With the help of optimal controller and PID (proportional integral derivative) the performance of the proposed controller is measured. The results of the proposed scheme is compared with different algorithms under same considerations.

Cluster based DE is proposed in this paper [29] by the authors with Gaussian based sampling and random based sampling. Modified DE is termed as MGRCDE. The proposed method enhances the local search operations having best quality in the subpopulation also maintain the population diversity also with final solution searching. Here, clustering helps to increase the convergence speed. 25 unconstrained benchmark functions are used to test the proposed method. It shows more efficient results comparing to other optimization techniques.

In this study [30] author surveys differential evolution for about 25 years considering near about 283 articles. In this paper journey of DE is explained with basic aspects such as mutation schemes, population generation, and variation in parameters, crossover schemes and hybridized variants along with different applications of DE.

In this study [31] properties and basic concept of DSSS scheme, mathematical concepts illustration of modulated signals spreading, essential characteristics in frequency and time domains etc. This book chapter gives a very good concept regarding direct sequence spread spectrum system.

To optimize spectral efficiency and also for high data rate communication scheduler approach is used by the authors in the paper [32, 33] in LTE (long term evolution) and OFDMA (orthogonal frequency division multiple access) wireless system.

Not only are that other different methods of modification of DE and also application in various fields along with in the field of wireless communication also reflected in [34–45].

3 The Proposed Method

3.1 Basic Differential Evolution Algorithm

The Fig. 1 shows the procedure of Differential Evolutionary algorithm. The mathematical explanation of differential evolution is as shown in the following.

Population Initialization:

\[ x_{n,j}^{g} = \left[ x_{n,1}^{g}, x_{n,2}^{g}, x_{n,3}^{g}, \ldots, x_{n,D}^{g} \right] \]  

Equation 1 represents the initial population having population size N where, g is the generation, n = 1, 2, 3, … N. \( x_{n,j}^{U} \), \( x_{n,j}^{L} \) are the upper and lower limit of \( x_{i} \) respectively.

Mutation
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\[ v_{n}^{g+1} = \left[ x_{1n}^{g} + F(x_{2n}^{g} - x_{3n}^{g}) \right] \]  

(2)

Mutation is the first step to create a new generation. Here, \( x_{1n}^{g}, x_{2n}^{g}, \) and \( x_{3n}^{g} \) are three random vectors. And weighted difference \( (x_{2n}^{g} - x_{3n}^{g}) \) is calculated by \( F \), \( F \) has the range between \([0, 2]\). \( v \) is the mutant vector.

Crossover:

\[ u_{n,i}^{g+1} = v_{n,i}^{g+1}, \quad \text{if } \text{rand}() \leq CR \text{ or } i = I_{\text{rand}} \]
\[ u_{n,i}^{g+1} = x_{n,i}^{g}, \quad \text{otherwise} \]

\[ i = 1, 2, 3, \ldots, D \quad \text{and} \quad n = 1, 2, 3, \ldots, N. \]

where, \( u \) is the trial vector, \( I_{\text{rand}} \) is randomly selected index having interval \([1, D]\) and \( CR \) is the crossover constant.

Selection:

\[ x_{n}^{g+1} = u_{n,i}^{g+1}, \quad \text{if } f(u_{n}^{g+1}) < f(x_{n}^{g}) \]
\[ x_{n}^{g+1} = x_{n,i}, \quad \text{otherwise} \]

(4)

Here fitness is checked by comparing the trial vector (\( u \)) and the original vector (\( x \)). If an acceptable result has been found the algorithm terminates, otherwise the mutation, crossover and selection is done again and so on.

3.2 Comparison of Two Different Modified DE

In this section at first two different modified DE are compared by applying it in engineering design problems. The difference between the modified DE is explained with the help of the flow diagrams as shown in Figs. 2 and 3.

Figures 2 and 3 describe the modification of DE, where initialization of the population is same in both the case but the mutation is varied as explained below.

a. Mathematical expression for Modified DE (using exponential scale factor)

The modified DE is differing from the basic DE as shown in the following steps.

Initialization:

In the beginning to generate the population, an external archive is generated to obtain better outcomes.

Let, \( P \) be the population, and let \( M \) be candidate solutions number, \( x_{ij}^{g} \) is a population member of \( P \) having dimension \( D \). \( i \) denotes candidate solution and \( j \) denotes dimension.

Where,

\[ i = 1, 2, 3, 4 \ldots M; \quad j = 1, 2, 3, 4 \ldots D; \]

\( P \) is taken from logistic map equation, logistic map equation is as shown in the Eq. 4.

\[ x_{n+1} = r \ast x_{n} \left( 1 - x_{n} \right) \]

(5)

\( x_{n} \) represents population for year \( n \), having range between 0 and 1, \( r \) represent increase or decrease rate of population, having range 0 to 4.
P is written as \( \{x_{1,j}, x_{2,j}, \ldots, x_{M,j}\} \).

Now, from that set of population P, minimal value \( x^L_j \) and maximal value \( x^U_j \) is calculated.

\[
\begin{align*}
x^L_j &= \min \{x_{i,j}\} \quad \text{where, } 1 \leq i \leq M \\
x^U_j &= \max \{x_{i,j}\} \quad \text{where, } 1 \leq i \leq M
\end{align*}
\]

Let, PP is the new set of population, in the range \( [x^L_j, x^U_j] \).

\[
y_{i,j} = x^L_j + \text{rand}() \times (x^U_j - x^L_j)
\]

(6)

After producing this external archived, now the first half of best set of population is generated by merging the both the sets of population P and PP and reassigned to P.
Then, OPP i.e. opposition based population is created as shown in the following

\[
OPP_{ij} = x^L_j + x^U_j - P_{ij}
\]  \hspace{1cm} (7)

Mutation: Mutation process is carried out using two steps.

Setp-1: To enhance the performance, here mutation scheme is adopted as shown below. DE/rand/1/bin method is used by the original differential evolution. But in this modified differential evolution algorithm, the scheme used is DE/best/1/bin which is elaborated in the following by mathematical terms.

\[
\nu^k_{i} = x^k_{best} + F(x^k_{i1} - x^k_{i2})
\]  \hspace{1cm} (8)

Fig. 3 Flow diagram of modified DE
Here, $x_{\text{best}}^k$ represents the best solution considering the whole population and $i_1 \neq i_2 \neq i_3 \neq i$, where $i_1$, $i_2$, $i_3$ have range between $[1, M]$, they all are different integer numbers. $F$ is the scaling factor.

Step-2: In basic DE, $F$ the scaling factor, CR the crossover rate are constant values, but in modified DE, $F$ is replaced by taking exponential scaling factor $f$. In DE, using scaling factor $(F)$ and crossover rate $(CR)$, exploration and exploitation are balanced. For greater value of $F$ and $CR$, in the search area, there is a high probability to skip the true solution. To overcome this drawback, the scale factor is replaced by exponential scale factor $f$ as show in the Eq. (9). During the stage of initial iteration, the value of $f$ will be high, which helps in the search area in exploration, after drop of some iterations, exponentially the value of $f$ will decrease, hence with reduced step size, the solution is now move and which enhances the exploitation skill of the algorithm. By using this approach, proper equilibrium between exploration and exploitation skills of the algorithm can be upheld.

$$f = 1/\exp(1 - (K - i)/K)$$ (9)

Here, $K$ represents maximum iteration number, $i$ represents current iteration.

b. Mathematical expression for Enhanced DE, EDE (Wavelet based DE)

In Fig. 3 Initialization part is same as the modified DE and mutation can expressed as follows

$$v_i^{k+1} = x_{\text{best}}^k + F(x_{i1}^k - x_{i2}^k), \quad \text{if } \delta < 0;$$
$$v_i^{k+1} = x_{i3}^k + F(x_{i1}^k - x_{i2}^k), \quad \text{if } \delta \geq 0. \quad (10)$$

Here, $x_{\text{best}}^k = \text{best solution}; i_1, i_2, i_3$ are not equal and are different integer numbers having range $[1, M]; \delta = \text{selection probability}. \text{Also, } F \text{ (scale factor) is not constant and}$

$$F = \delta = \psi_d(\theta) = \frac{1}{\sqrt{d}} \psi\left(\frac{\theta}{d}\right)$$ (11)

where $d = e^{\ln(\lambda) \times (1 - \iota)^\iota_{\text{wm}}} + \ln(\lambda)$ and $\lambda$ = upper limit of $d$, $i$ = current iteration number, $I$ = total iteration number, $\iota_{\text{wm}}$ = shape parameter, is a monotonically increasing function.

And detail mathematical expression of wavelet transform is given in [23].

3.3 Optimization of Spreading Code Using Modified DE

The flow diagram of the optimized spreading code is as shown the Fig. 4

As wavelet-based DE (Enhanced Differential Evolution, EDE) shows better results as explained in section 4 than exponential based DE, Logistic map based spreading sequences are optimized using the wavelet-based DE as shown in the flow diagram in Fig.4. Binary bits are generated using the thresholding method (method 1) and integer to bit conversion method (method 2) [23]. Properties (Mono bit test, run-length test, computational time) of optimized generated bits are compared with the non-optimized one [1] as shown in the Table as shown in section 4.
3.4 Application of Optimized Spreading Code in Static and Dynamic Direct Sequence Spread Spectrum System to Calculate BER (Bit Error Rate) for Signal Detection

Figures 5 and 6 show the static and dynamic DSSS respectively. Figure 5 displays the static DSSS with an optimized logistic map based spreading code and Fig. 6 shows that the dynamic DSSS with optimized logistic map based spreading code. The basic fundamental of DSSS is that binary bits are spread over the channel bandwidth. First, from a random source data is generated. It consists of a series of ones and zeros. In modulation data bits are mapped into symbol vector. The modulation scheme used in this work is BPSK (binary phase shift keying) [1]. The modulated data is spread by an optimized logistic map based spreading code in the transmitter section in Fig. 5. After passing through the nonlinear channel, the received signal is de-spreaded using the same optimized spreading code and then demodulated using the BPSK demodulator. The word dynamic is used in Fig. 6 because the optimized spreading code is not fixed, the length is changed with the BER (bit error rate) value obtained comparing to the threshold value.
Mathematical equations of the proposed system are explained in the following.

1. Received signal:

\[ k_{m,n}(b, \theta) = f_1(b(n), d(n)).S_n \ast H_{m,n}(b, \theta) + N \]  

where

- \( f_1(b(n), d(n)) \) is a modulation process,
- \( P(b, \theta) = Rayleigh_{m,n}(1 + b + b^2 + \cos \theta) \) is the channel matrix for b sample value and \( \theta \) is the phase with nonlinear terms,
- \( G_n = Step(q_n) \) with \( q_{n+1} = r \ast q_n (1 - q_n) \) is an optimized logistic map-based sequence with \( r = 3.582 \). (Optimization algorithm is wavelet-based differential evolution)

2. In recovery,

   While \((BER < \text{Threshold})\).
   - Update \( G_n \) and repeat \( k \) as in step 1.

4 Parameter Settings and Experimental Results

To compare both modified algorithms of DE and to analysis, the efficiency as explained in Sect. 3, the important benchmark functions used are Perm function, Levy function, Schwefel function, Sum of different powers function, Trid function, Griewank function, Sphere function, Ackley function, Rastrigin function, and Zakharov [23]. Table 1 shows the simulation parameter. The comparative outcomes are as shown in Table 2, \( f_1 \) is Gas transmission compressor design, \( f_2 \) is Optimal capacity of gas production facilities and \( f_3 \) is the Design of a gear train [23]. Tables 2 and 3 explains the comparative study of wavelet based DE and exponential based DE with existing modified DE [DE, Pro. DCPCX (Differential evolution with probabilistic parent centric...
Optimization of Spreading Code Using Modified Differential Evolution (crossover), DCPCX (Differential evolution with parent centric crossover)] using three real time optimization problems with the help of Mean, Standard Deviation and number of function evaluations. f2 and f3 of wavelet based DE (EDE) gives better result (considering mean and standard deviation) than exponential based DE (Modified DE) from Table 2. Also from Table 3, number of function evolution (NFE) for f2 and f3 is less for EDE than Modified DE, that means speed of EDE is more than modified DE, it is clear from Table 3 that wavelet-based DE converges more quickly than exponential based DE. Hence, from Tables 2 and 3 it is clear that wavelet-based DE gives better results than exponential DE considering real-time engineering design problems [23, 46]. Further, a comparative study is done for optimized and non-optimized binary sequences considering the properties of generated bits as shown in Table 4. Table 4 shows that, when we consider method 1 (thresholding) and method 2 (integer to bit conversion) for both optimized and non-optimized bits, method 2 gives better results than method 1 for both mono bit test and run-length test. But computational time required is more in case of the thresholding method. Also when we consider optimized and non-optimized binary sequences, it is clear from Table 4 that optimized binary sequences show better mono bit test and run-length test properties. Hence optimized version of method 1 is used in a DSSS. Figure 7 shows the BER curves for static non-optimized, static optimized and dynamic optimized DSSS. From Fig. 7 we can say that static optimization gives better results than static non-optimization because the BER curve for static optimization is more close to the theoretical value. Also when we consider static and dynamic, the dynamic is more close to the theoretical one. Hence we can say from the analysis of the result that dynamic optimization gives better results than static optimization or static non-optimization. Figure 8 shows the BER curves for orthogonal, static optimized and dynamic optimized spreading sequence and it is clear from Fig. 8 that dynamic optimization is more closer to the theoretical value comparing to the remaining BER curves means gives the better result. But when we compare static optimization and orthogonal, orthogonal gives the better result than the static optimization. Figure 9 explains the BER curves for optimized spreading sequence for DPSK (Differential Phase Shift Keying), BPSK (Binary Phase Shift Keying) and QPSK (Quadrature Phase Shift Keying) modulation and the BER curves describe that BPSK and QPSK almost gives the same BER and better than DPSK modulation. Figures 10, 11 and 12 show the convergence

| Sl. no | Item                          | Description                                      |
|--------|-------------------------------|--------------------------------------------------|
| 1      | Modulation type               | BPSK, QPSK, DPSK                                 |
| 2      | Data block size               | Between 1000 and 10,000 (bits)                   |
| 3      | Logistic map code             | Static, Static optimized, Dynamic optimized, Orthogonal |
| 4      | Value of r in the logistic map| 3.582                                            |
| 5      | Channel type                  | AWGN(Additive White Gaussian Noise), Rayleigh (nonlinear) |
| 6      | No. of trials per sequence length | At least 10                                    |
| 7      | Modified DE                   | Wavelet-based DE                                 |
| Func | Dim | DE Mean | Standard deviation | DCPCX Mean | Standard Deviation | Pro. DCPCX Mean | Standard deviation | Modified DE Mean | Standard deviation | EDE Mean | Standard deviation |
|------|-----|---------|-------------------|------------|-------------------|-----------------|------------------|------------------|------------------|-----------|------------------|
|      |     |         |                   |            |                   |                 |                  |                  |                  |           |                  |
| f1   | 3   | 2.96E+6 | 0.264829          | 2.98E+6    | 0                 | 2.96E+06        | 4.66E−10         | 1.63E+06         | 8.95E−11         | 2.74E+07 | 5.34E−09         |
| f2   | 2   | 169.844 | 0.000021          | 169.846    | 2.84E−14          | 169.844         | 2.84E−14         | 170.213          | 6.10E−14         | 169.002 | 4.33E−15         |
| f3   | 4   | 1.76E−08| 3.52E−08          | 6.57E−09   | 1.65E−24          | 2.68E−08        | 3.31E−24         | 9.43E−10         | 4.02E−24         | 6.84E−12 | 6.93E−19         |

The figures reflected in bold inside table are compared with DE, DCPCX, Pro. DCPCX with proposed method Modified DE & EDE for f1,f2 & f3 considering standard deviation & mean.
speed graph of function f1, f2, and f3 for different algorithms. All the simulations are done using Matlab [47].

5 Conclusion

DE with enhanced parameters can play a vital role to solve the realistic optimization problems and application in wireless communication techniques. To optimize chaos code differential evolutionary algorithm can be considered because it has the property of random search, requires only fewer parameters setting, high performance and valid to complex optimization problems. Also, hybridization of stochastic algorithm is important because, to improve the convergence speed, to balance the exploration (diversification) and exploitation (intensification) process, to avoid trapping in local optima and to improve the quality of the solutions. Static optimization is improved by 40% than non-optimized static, dynamic optimization is improved by 70% than static optimization but orthogonal is showing 33% improvement comparing to static optimization and dynamic optimization is improved by 56% than orthogonal one. From the outcomes of the proposed system, it is clear that the optimized chaos code using modified DE can be used as a spreading code which gives better results than non-optimized spreading code and orthogonal spreading code. Hence, the work explores the spin-offs that can be obtained from optimized link oriented chaos system supported wireless techniques. In future, the modified DE can be used in massive MIMO system also can be used over OFDM system.

| Func | Dim | NFE (DE) | NFE(DEPCX) | NFE (Pro DEPCX) | Modified DE | EDE |
|------|-----|----------|-------------|----------------|-------------|-----|
| F1   | 3   | 8438     | 882         | 1566           | 798         | 820 |
| F2   | 2   | 306      | 228         | 318            | 221         | 202 |
| F3   | 4   | 463      | 312         | 300            | 249         | 211 |
Table 4  Comparative study of Properties of the generated bit sequence

| Test               | Properties of non-optimized generated bit | Properties of optimized generated bit |
|--------------------|------------------------------------------|--------------------------------------|
|                    | Method-1                                  | Method-2                             | Method-3                             | Method-4                             |
| Mono bit Test      | No. of Zeros = 66                         | No. of Zeros = 41                    | No. of Zeros = 62                    | No. of Zeros = 43                    |
|                    | No. of Ones = 34                          | No. of Ones = 59                     | No. of Ones = 38                     | No. of Ones = 57                     |
|                    | Out of 100 bits                           | Out of 100 bits                      | Out of 100 bits                      | Out of 100 bits                      |
| Run Length test    | Run is 5 out of 20 bits                   | Run is 5 out of 20 bits              | Run is 6 out of 20 bits              | Run is 7 out of 20 bits              |
| Computational      | CT is 1.02 s                              | CT is 1.94 s                         | CT is 1.38 s                         | CT is 2.11 s                         |
| Complexity         |                                          |                                      |                                      |                                      |
Fig. 7 BER curves for static non-optimized, static optimized and dynamic optimized DSSS

Fig. 8 BER curves for orthogonal, static optimized and dynamic optimized spreading sequence

Fig. 9 BER curves for optimized spreading sequence for DPSK, BPSK and QPSK modulation
Fig. 10 Number of function evaluation for function f1

Fig. 11 Number of function evaluation for function f2

Fig. 12 Number of function evaluation for function f3
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Code availability (software application or custom code) Explained with the help of flow diagram.

Declarations

Conflict of interest None.

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