Application of Asynchronous DE with Trigonometric Mutation in Engineering Design Problems

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***Abstract:** Asynchronous Differential Evolution (ADE) algorithm, a variation of Differential Evolution (DE) algorithm works asynchronously. It supports parallel optimization and strong exploration because ADE algorithm updates the population instantly when a vector with better fitness is found. ADE working is quite similar to Differential Evolution (DE) except the instant population updation feature. In this paper trigonometric mutation embedded ADE (ADE-TMO), a hybridized algorithm is tested over four unconstrained engineering design problems.*

***Index Terms:** Differential evolution, asynchronous differential evolution, trigonometric mutation, engineering design application.*

I. INTRODUCTION

Many metaheuristic algorithms have been introduced in the past years [2]. Differential evolution (DE) algorithm was introduced in 1995 [1]. DE has been used especially for continuous optimization and has unfolded as a powerful optimizer. The Differential Evolution works upon a synchronous generation based evolution strategy [1]. It is proved as a powerful algorithm in the field of various engineering like, mechanical[3], pattern recognition [4], communication [5] and in various other fields [4-8].

In this paper ADE algorithm, which depends on DE with some alteration is discussed. ADE-TMO algorithm [21] is tested over four unconstrained design problems in the field of engineering.

ADE working is based on DE with the change in the concept of generation increments. Unlike DE, there are no generations in ADE. The population evolves in one generation only. The evolution in ADE is based on individual target vector. The target and trial vector's fitness is compared and without any time lag the population is updated with better vector. In DE algorithm, the more fit vector can participate in evolution in the next generation only. ADE has shown better performance than DE over various performance metrics [18][16]. The layout of the paper is : Section 2 details ADE algorithm's working and ADE-TMO algorithm. Section 3 summarizes the parameter settings and engineering problems considered. In section 4 results are presented on engineering application of the proposed algorithm. In last section conclusion and future scope has been mwntioned.

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II. ASYNCHRONOUS DIFFERENTIAL EVOLUTION

In most cases ADE gives better results than DE and its many variants [15]. ADE algorithm has been presented with modifications in the past years. The analysis results proved that these algorithms with modifications perform well as compared to ADE and other metaheuristic algorithms [9-15, 21].

A. Basic ADE

Initialization of Population

Population is initialized having NP candidate solutions:

$$\boldsymbol{X_i} = \{\boldsymbol{x_{1,i}}, \boldsymbol{x_{2,i}}, \ldots\ldots, \boldsymbol{x_{D,i}}\} \quad \textbf{(1)}$$

here i = 1, 2,…, NP; and represents the i^{th} individual.
D is problem's dimension.
i^{th} vector's j^{th} component is:

$$x_{ji} = a_j + rand_j(b_j - a_j) \quad \textbf{(2)}$$

$rand_j$ is a known as number which is uniformly distributed and lies between (0,1) and manifested separately for each component of a vector.

Mutation

The mutation is performed on randomly chosen target vector (X_i) to form a mutant/donor vector (V_i) with the help of randomly chosen mutually exclusive numbers r_1, r_2, r_3 and a scaling factor F.

$$\boldsymbol{V_i} = \boldsymbol{x_{r1}} + \boldsymbol{F}(\boldsymbol{x_{r2}} - \boldsymbol{x_{r3}}) \quad \textbf{(3)}$$

The randomly chosen numbers are also different from i. F lies somewhere between 0 and 1.

Crossover

The trial vector (U_i) is constructed by exchanging the donor vector (V_i) component by target vector (X_i) to increase the population diversity.

$$\boldsymbol{U_{j,i}} = \begin{cases} \boldsymbol{V_{j,i}\ if\ rand_{i,j}\ [0,1] \le C_r\ or\ j = j_{rand}} \\ \boldsymbol{X_{j,i}\ Otherwise} \end{cases} \quad (4)$$

here j = 1,..., D
$j_{rand} \in \{1,\ldots, D\}$,for each i it is chosen once.
Cr is crossover probability and ranges from 0 to 1.
If $rand_{i,j}$ [0,1] is less than or equal to Cr, the U_i will have parameter from V_i; else from X_i.

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Selection Operation

This operation decides which vector will be a part of the population as :

$$X_{i,G} = \begin{cases} U_{i,G} \text{ if } f(U_{i,G}) \leq f(X_{i,G}) \\ X_{i,G} \text{ Otherwise} \end{cases} \quad (5)$$

B. ADE-TMO Algorithm:

// Population Initialization

$$X_i = \{x_{1,i}, x_{2,i}, \ldots\ldots, x_{D,i}\}$$

do {

i=select_target_vector ();

// Mutation Operation

if rand[0,1]< P_{TMO} then

$$V_i = \frac{(X_{r1} + X_{r2} + X_{r3})}{3} + (p_2 - p_1)(X_{r1} - X_{r2}) + (p_3 - p_2)(X_{r2} - X_{r3}) + (p_1 - p_3)(X_{r3} - X_{r1})$$

else

$$V_i = x_{r1} + F(x_{r2} - x_{r3})$$

// Crossover Operation

for (j=0; j<D; j=j+1)

$$U_{j,i} = \begin{cases} V_{j,i} \text{ if } rand_{i,j}[0,1] \leq C_r \text{ or } j = j_{rand} \\ X_{j,i} \text{ Otherwise} \end{cases}$$

// Selection Operation (for next iteration)

$$X_{i,G} = \begin{cases} U_{i,G} \text{ if } f(U_{i,G}) \leq f(X_{i,G}) \\ X_{i,G} \text{ Otherwise} \end{cases}$$

} while the termination criteria is met.

Figure 1. *ADE-TMO Algorithm* [21]

Fig. 1 represents the algorithm used for engineering design problems with two values of P_{TMO}.

III. PARAMETER SETTINGS

The proposed work is evaluated over four unconstrained design problems in the field of engineering. The parameter settings of algorithm are discussed below in subsection.

A. Parameter Settings

Trigonometric mutation probability (P_{TMO}): Prob1= 0.3; Prob2=0.4;

Population Size (NP): 20;

Value to reach (VTR) : 10^{-4} ;

Cross-over Rate (C_r) : 0.9;

Dimension (D): 30;

Scaling (F): 0.5;

Max. no. of function evaluations: 10^6

B. Real Life Engineering Problems

The algorithm performance for considered probabilities is tested over four unconstrained engineering design problems. The problems are: (i) Optimal capacity of gas production facility [18], (ii) Gas transmission compressor design [18], (iii) Design of gear train [19] and (iv) Frequency modulation sound parameter identification [20].

F1: Gas Production Facility

This problem calculated optimum capacity of production facilities to make a system to store and produce oxygen.

$$\boldsymbol{Min\, f(x) = 61.8 + 5.72x_1 + 0.2623\left[(40 - x_1)\ln\left(\frac{x_2}{200}\right)\right]^{-0.85} + 0.087\,(40 - x_1)\ln\left(\frac{x_2}{200}\right) + 700.23x_2^{-0.5}} \quad (6)$$

Subject to : $x_1 \geq 17.5, x_2 \geq 200$

Bounds: $17.5 \leq x_1 \leq 40, 300 \leq x_2 \leq 600$

F2: Gas Transmission Compressor Design

Mathematically, the above stated problem is represented as follows:

$$\boldsymbol{Min\, f(x) = 8.61 \times 10^5 \times x_1^{\frac{1}{2}} x_2 x_3^{-\frac{2}{3}} (x_2^2 - 1)^{-\frac{1}{2}} + 3.69 \times 10^4 \times x_3 + 7.72 \times 10^8 \times x_1^{-1} x_2^{0.219} - 765.43 \times 10^6 \times x_1^{-1}} \quad (7)$$

Bounds: $10 \leq x_1 \leq 55, 1.1 \leq x_2 \leq 2, 10 \leq x_3 \leq 40$

F3: Frequency Modulation Sound Parameter Identification

The parameters a_1, a_2, a_3, w_1, w_2, w_3 are satisfied in this problem as given below:

$$\boldsymbol{y(t) = a_1 \times \sin\left(w_1 \times t \times \theta + a_2 \times \sin\left(w_2 \times t \times \theta + a_3 \times \sin(w_3 \times t \times \theta)\right)\right)} \quad (8)$$

where $\theta = (2\pi/100)$ and the fitness function is given as:

$$f(a_1, w_1, a_2, w_2, a_3, w_3) = \sum_{t=0}^{100} (y(t) - y_0(t))^2 \quad \textbf{(9)}$$

And the model data are given as:

$$\boldsymbol{y_0(t) = 1.0 \times \sin\left(5.0 \times t \times \theta + 1.5 \times \sin\left(4.8 \times t \times \theta + 2.0 \times \sin(4.9 \times t \times \theta)\right)\right)} \quad (10)$$

The range of each parameter is (-6.4,6.35).

F4: Designing of Gear Train

In gear train design gear ratio must be close to 1/6.931 as much as possible. The integer number of teeth's are used and range from 12 to 60. Gear train is designed as follows:

$$Min\, f = \left\{\frac{1}{6.931} - \frac{T_d T_b}{T_a T_f}\right\}^2 = \left\{\frac{1}{6.931} - \frac{x_1 x_2}{x_3 x_4}\right\}^2 \quad \textbf{(11)}$$

Subject to $12 \leq x_i \leq 60, i = 1,2,3,4.$

$$[x_1, x_2, x_3, x_4] = [T_d, T_b, T_a, T_f]$$

Where, A, B, D and F gears have T_a, T_b, T_d and T_f teeth respectively.

IV. RESULTS

Table 1, 2, 3 and 4 demonstrate the results for the considered problems for two values of probabilities.

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Table 1. Simulation Results for F1

Optimal Capacity of Gas Production Facilities		
Item	**Prob1**	**Prob2**
x1	17.50	17.50
x2	599.99	598.99
NFE	1.67e+03	1.72e+03
F(x)	169.843	169.843

Table 2. Simulation Results for F2

Gas Transmission Compressor Design		
Item	**Prob1**	**Prob2**
x1	53.4470	52.5635
x2	1.1901	1.1862
x3	24.7186	24.7047
NFE	2.61e+03	3.39e+03
F(x)	2.97e+06	2.96e+06

Table 3. Simulation Results for F3

Frequency Modulation Sound Parameter Identification		
Item	**Prob1**	**Prob2**
x1	0.7696	-0.4283
x2	-1.6508	-4.9442
x3	2.0246	-0.5998
x4	3.3071	1.9526
x5	0.4750	-2.8963
x6	3.3269	-3.9668
NFE	5.11e+03	4.15e+03
F(x)	10.4029	3.9762

Table 1-4 summarize that ADE-TMO is capable of solving the problems since the values of variables for all problems are in specified bound. Hence it can be observed from Table 5.26 - Table 5.29 ADE-TMO performs up to mark for both the probabilities P1 and P2. But when the results for both probabilities are compared, P2 performs better than P1.

Table 4. Simulation Results for F4

Design of Gear Train		
Item	**Prob1**	**Prob2**
x1	14	16
x2	34	19
x3	60	49
x4	55	43
NFE	1.52e+03	1.44e+03
Gear ratio	0.14424	0.14428
F(x)	1.55e-10	2.71e-12

V. CONCLUSION & FUTURE SCOPE

The presented work tests the ADE-TMO algorithm with two values of P_{TMO} over a set unconstrained engineering design problems. Further ADE-TMO can be tested on constrained and multiobjective problems in future.

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