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# Industrial Application of Differential Evolution Algorithm

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***Abstract*—Here, we presented, the use of differential evolution algorithm in industrial applications. The differential evolution algorithm is widely used to solve direct, continuous space optimizations problems. The application of DE is present in almost all fields of engineering problems. One real life problem, from the field of electronic engineering name frequency modulation for sound waves synthesis is used to show the efficiency of differential evolution algorithm. The results are further evaluated on the parameter name success rate and success performance , they shows that the DE have very fast convergence rate and having ability to solve the given problem**

***Index Terms*—Evolutionary algorithm, sound waves, multi-model problem**

## I. INTRODUCTION

A differential evolution algorithm (DE) [1] [2] is heuristic approach for optimizing the nonlinear and non-differentiable continuous space problems. DE converges faster and with more certainty than many other acclaimed global optimization methods. It requires few control variables, is robust, easy to use, and lends itself very well to parallel computation hence it is very promising to solve engineering optimization problems [3] The application of differential evolution algorithm can be easily found in real life problems in the field of .electronic engineering [4] [11] [15] [16][23] , electrical engineering [5] [8] [9] [10] [13][19] , combinatorial mathematics [6],civil engineering [7] [17] , aeronautical engineering [12] [22] , operation research [14] , education sector [18],logistic design [20] [21] ,other soft computing techniques [24] .In [4], the problems of radio resource allocation for Orthogonal Frequency Division Multiple Access (OFDMA) systems are addressed by presenting and analyzing the base station allocation of subcarriers and adaptive modulation. Author proposed an adaptive radio resource allocation method based on differential evolutionary algorithm for multiuser OFDMA system . the proposed method have high convergence rate as compare to SDE, because in proposed method, author have used elitist selection and add some fit individuals to the population Simulation results show that proposed algorithm better than static subcarrier allocation schemes TDMA in multiuser OFDMA system. The critical task for current and future scenario in mobile communication is Frequency Assignment in the planning of the GSM networks is address [5] and solve by using a hybrid Differential Evolution (DE) algorithm Author give a detail explanation about the hybridization method applied to DE.

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The results that are shown use accurate interference information. The provided information very applicable in real world because it is adopted and represents in a real GSM network, granting. The proposed method give better results as compare to o0ther compared traditional methods. By enhancing the differential evolution algorithm by using quantum bits and state interference [6] is used for solving the N-queens problem is presented. The N-queens problem aims at placing N queens on an NxN chessboard, in such a way that no queen could capture any of the others. The proposed algorithm is a novel hybridization between differential evolution algorithms and quantum computing principles. The proposed method have a remarkable efficiency and good results. Safety factor with minimal value is primary requirement for stability analysis in soil. The Standard differential evolution with improve coefficient mutation method is proposed [7] to locate the dangerous slip surface. The method is compared with Zolfaghari's method , it has found that the slip surface obtained by proposed approaches more close to the soft layer than that of Zolfaghari approach. A heuristic approach name workflow planning using multi objective differential evolution algorithm [8] is proposed to handle scheduling application on global grid. It generate the trade-off scheduling according to user QoS requirement (time and cost). The proposed method give better spread of solution as compare to other methods. The standard differential evolution is used to minimize the total fuel cost of thermal generating units, subject to the usual constraints, in [9] load dispatch problem. The proposed method is more effective than the other methods. Using the absolute weighted difference between the two points and instead of using a fixed scaling factor F, use a scaling factor following the Laplace distribution, five new mutation schemes for the basic DE algorithm named MDE1, MDE2, MDE3, MDE4 and MDE5 are proposed by authors [10]. Further, these proposed schemes are validated empirically on a suit of ten benchmark problems having box constraints and real life electrical engineering problem dealing with the optimization of directional over-current relay settings. The proposed schemes are compatible for solving the real life problem and improves the convergence rate of the DE algorithm and also maintains the quality of solution. A New Self-adaptive DE (SADE) based method [11] is used to solve real-valued antenna and microwave design problems – including linear-array synthesis, patch-antenna design and micros trip filter design. The scale-up study of proposed scheme show that DE algorithms outperform the PSO variants in terms of finding best optima on the bases of statistical results and convergence speed. A new method in SDE, which using fixed points toward converges with probability for an infinite number of generations is use to solve the space [12] trajectory problem.

The novel algorithm is then extended with a guided restart procedure that further increases the performance, reducing the probability of stagnation in deceptive local minima. A modified Differential Evolution [13] (MDE) algorithm is proposed to solve the problems of substation location optimization based on GIS with geographic information, the rural power network characteristic and its located complex geographical environment, these complexites make the given solution more effective and feasible.. The proposed algorithm has improve the efficiency of modified differential evolution for adjusting the inertia scaling factor F scope purposefully to different function. The two variants of differential evolution (DE) [14] algorithms with a “blind” variable neighborhood search (VNS) algorithm are presented to solve the generalized assignment problem (GAP)in continuous and discrete space , the proposed algorithms enhance the solution quality, especially to end up with feasible solutions. The new proposed algorithm are able to generate competitive results to its discrete counterpart. A Differential Evolution having effective population initialization strategy and a double neighborhood structure local search technique is used to solve management problem in mobile computing [15]. The proposed algorithm is performing better than other counter parts. A selective neural network ensemble method using discrete differential evolution [16] algorithm is proposed to improve the accuracy of short-term load forecasting part of individual networks is optimized selected to ensemble and an entropy method is used to determine the integrated weighted coefficient of component neural networks according to the variability of prediction error sequences. The experiments show that the proposed approach has higher accuracy and stability. The differential evolution (DE) algorithm [17] with dynamic parameter adjustment strategy that guarantees the multiplicity of colony in the initial computation period and enhances the optimization speed of the algorithm is used to solve the substation location optimization problem for a distribution network. A discrete differential evolution algorithm [18], with effective coding strategy (generate high quality test-sheets) for computer-aided testing. Computer-aided testing plays an important role in computer-aided testing systems. The proposed algorithm used a series of item banks with different scale for testing and gives better results than other compared algorithms. The available transfer capability (ATC) [19] model with differential evolution algorithm (IDE) calculation based on transient stability constrained optimal flow (TSCOPF) is used to solve imprecision problem in confirming boundaries of the rotor angle . The better global search capability the faster rapidity of convergence and search accuracy were assured through the introduction of the constant idea of simulation anneal tactics and time-variation cross probability. The simulation results indicate that the improved strategy of DE algorithm is simple and effective, and the improved DE algorithm used to calculate ATC based on TSCOPF is faster and higher accuracy. Differential evolution algorithm is applied to solve a mixed integer nonlinear programming model including forward logistics and reverse logistics[20]. Result shows the algorithm has a rapid convergence rate. The problem [22] of conventional Linear Quadratic Gaussian with Loop Transfer Recovery (LQG/LTR) controller design, where, designer experiment with four different weighting matrices by trial-and-error method in order to get the flying quality requirement and the robustness. The differential evolution based LQG/LTR flight controller optimal design method is proposed. The simulation results show the high effectiveness of this optimal design method. A new method based on differential evolution algorithm to design two-dimensional synthetic aperture microwave radiometer circle array is proposed. The experimental results show that the differential evolution algorithm obtains a better solution and observably decrease computational run time as compared to other algorithms. An adaptive differential evolution algorithm with multiple trial vectors is used to for train artificial neural networks, named [24] , DE-ANNT+. It allows training an artificial neural network of arbitrary architectures and it offers a non-differentiable neuron activation function

## II. DIFFERENTIAL EVOLUTION ALGORITHM

Differential evolution (DE) is a novel parallel direct search method, which start with NP parameter vectors as a initial population: $x_i$, i = 1, 2,3 . . . . . NP. NP doesn't change during the evolution. If there is no prior information, then initial population is chosen randomly, otherwise, a uniform probability distribution use for initial population generation. After generation of initial population then next step is population evaluation. Each member of initial population is evaluated by using given fitness function and has a fitness value. DE generates new parameter vectors by adding the weighted difference between two population vectors to a third vector, called mutation.

### A. Mutation

For each target vector x i,, i = 1, 2, 3 . . . NP, a mutant vector is generated according to

$$v_i = xr_1 + F * (xr_2 - xr_3) \tag{1}$$

Whereas integers $r_1$, $r_2$, $r_3$ ϵ 1. . . NP, mutually different from each other and F > 0 ϵ [0, 2] The randomly chosen integers $r_1$, $r_2$ and $r_3$ are also chosen different from the running index ‘i’ . F is a real and constant factor which controls the amplification of the differential variation.

The mutated vector’s parameters are then mixed with the parameters of another predetermined vector-the target vector, to yield the so-called trial vector. Parameter mixing is referred to as crossover.

### B. Crossover

It increases the diversity of the perturbed parameter vectors. Here the trial vector $u_i = (u_1, u_2 . . . u_D)$ is formed, where

$$u_{j,i} = \begin{cases} v_{j,i} & \text{if } (randb(j) \leq CR) \text{ or } j = rnbr(i) \\ x_{j,i} & \text{if } (randb(j) > CR) \text{ and } j \neq rnbr(i) \end{cases} \tag{2}$$

j = 1, 2 . . . D: randb(j) is the jth evaluation of a uniform random number generator ϵ [0, 1].CR is the crossover constant ϵ [0,1]. rnbr(i) is a randomly chosen index ϵ 1,2….D which ensures that ui gets at least one parameter from vi If the trial vector yields a lower cost function value than the target vector, the trial vector replaces the target vector in the following generation. This last operation is called selection.

### *C. Selection*

To decide whether or not new vector should become a member of next generation, the trial vector u I is compared to the target vector x I using the greedy criterion. If vector u i, yields a smaller cost function value than x i, then x i, is set to u i; otherwise, the old value xi, is retained Each population vector has to serve once as the target vector so that NP competitions take place in one generation. This process is repeated until the stopping criteria do not satisfy.

### *D. Other variants of DE*

There are number of variants in DE. In order to represent the variants the following notation is used ; DE=x/y/z is
Where as

- x: The vector to be mutated which currently can be "rand" (a randomly chosen population vector) or "best" (the vector of lowest cost from the current population).
- y: Number of difference vectors used.
- z: The crossover scheme.

TABLE I. STRATEGIES OF DE

| Sr. No | Strategy | Sr. No | Strategy |
|---|---|---|---|
| 1 | DE/best/1/exp | 6 | DE/best/1/bin |
| 2 | DE/rand/1/exp | 7 | DE/rand/1/bin |
| 3 | DE/rand-to-best/1/exp | 8 | DE/rand-to-best/1/bin |
| 4 | DE/best/2/exp | 9 | DE/best/2/bin |
| 5 | DE/rand/2/exp | 10 | DE/rand/2/bin |

## III. EXPERIMENTAL ANALYSIS

Frequency-Modulated (FM) sound wave synthesis has an important role in several modern music systems and to optimize the parameter of an FM synthesizer is a six dimensional Optimization problem where the vector to be optimized is $x = \{a_1, \omega_1, a_2, \omega_2, a_3, \omega_3\}$ of the sound wave

$$\mathbf{y(t) = a_1.\sin(\omega_1.t.\theta + a_3\sin(\omega_2.t.\theta + a_3\sin(\omega_3.t.\theta))).}\ \textbf{(3)}$$

The problem is to generate a sound similar to target sound

$$\mathbf{y_0(t) = (1.0).\sin((5.0).t.\theta - (1.5).\sin((4.8).t.\theta - (2.0)\sin(4.9).t.\theta).}\ \textbf{(4)}$$

This problem is a highly complex multimodal one having strong epitasis', with minimum Value $f(\overrightarrow{X_{sol}}) = 0$, where , $\theta = 2\pi/100$ and the parameters are defined in the range [-6.4,6.35] The fitness function is the summation of square errors between the estimated wave and the target wave

$$f(\vec{X}) = \sum_{t=0}^{100}(y(t) - y_0(t))^2 \qquad (5)$$

The standard differential evolution is used to solve the parameter estimation frequency modulated sound waves problem The value of control parameters are sets as NP=20, F=0.8, Cr=0.9 and maximum function evaluation = 3*106 .Throughout the experimentation the value of F, Cr is fixed. For all problems DE executed for 50 times. The performance of the each method is evaluated as Success rate I,e Number of successful runs/Total number of runs, Success Performance, i.e, Average of Max function evaluation of successful runs/ success rate , Minimum value of function and Max function evaluated for min value.It has found that the success rate is 1. I,e all the time the standard differential evolution is able to solve Parameter Estimation for Frequency-Modulated (FM) Sound Waves problem with 5380 functions evaluations.

## IV. CONCLUSION

Differential evolution algorithm is parallel, direct search and easy to use optimization algorithm . It has very wide span of usability in the area of electronic engineering , electrical engineering , civil engineering , aeronautical engineering, and other related fields. Areal life having multi-model natured optimization problem name frequency modulation in sound wave synthesis is solving by using SDE. The stimulation shows the fast convergence rate and problem solving capability of algorithm

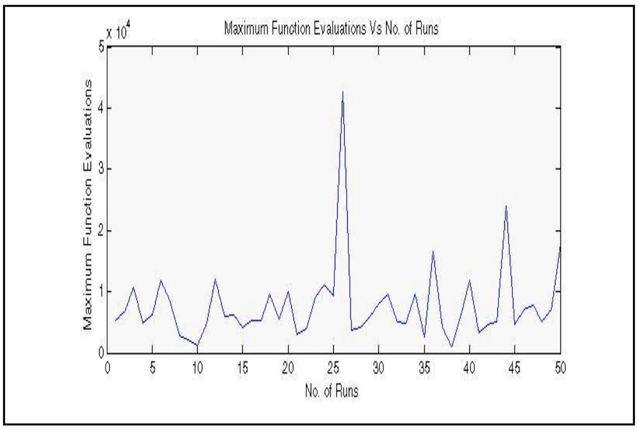


FIGURE I. MAXIMUM FUNCTION EVALUATION VS NO. OF RUNS

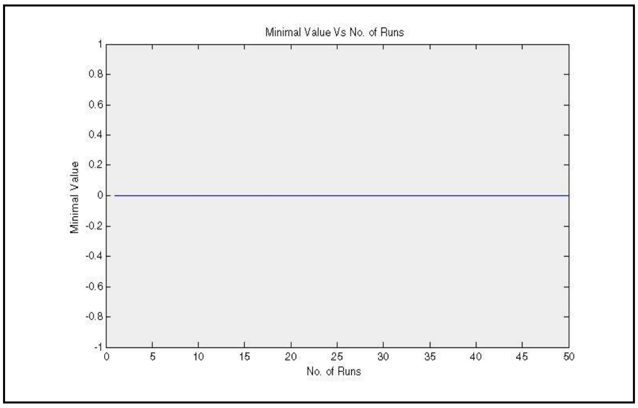


FIGURE II. MINIMAL VALUE VS NO. OF RUNS

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