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A Survey on Optimized Wireless Communication Techniques

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ABSTRACT:

Differential Evolution (DE) after its inception in 1995 has become one of the most recurrently used algorithms to solve the most complex problems related to optimization. Because of its litheness and adaptability, many customized variants of DE have sprung up and is used to solve a variety of real-life, test problems. In this study, a survey is done on the 18 years of existence of DE. The survey uses more than100 research articles to show the journey of DE through the basic aspects of population generation, mutation schemes, crossover schemes parameter variation and hybrid variants alongside many successful applications of DE in different fields which also includes wireless communication. The main aim is to provide an extended summary of the existence of DE over 18 years and the applications intended to be used by the interested parties. It is expected that this current survey will generate interest for the new upcoming users with respect to the philosophy that DE upholds and also will duly guide the exp experienced researchers.

KEYWORDS—Optimization, Differential Evolution, Application of DE, DE variants, Wireless Communication.

I. INTRODUCTION

Optimization helps in the decision making, or more aptly, is a major quantitative tool in the process of decision making, where are taken to optimize an objective or one or more objectives under defined circumstances. It may be said that optimization problems are found everywhere in nature as most of the real-life problems can be shown as optimization models, which involves many criteria as well as objectives. DE is the core of numerous fields like Mathematics, Engineering Physics, Computational Science, Operations Research, even Economics and Biology, etc. as well [1]. As an area of research, Optimization is wide, which uses a distinct method to solve a particular class of problem, for example, Integer Programming Problem (IPP), Linear Programming Problem (LPP), Non-convex optimization or Quadratic Programming Problem (QPP) etc. But the problem arises when it gets difficult to identify exactly is the nature of the problem at hand and thus it becomes very difficult to choose the appropriate method to reach a solution. Researchers are thus focusing on generic algorithms which can be used to solve a wide category of problems [5]. The past few decades saw a rise in such general-purpose algorithms which can be put under the umbrella term of Meta-heuristics [2]. In [50-55] discus various clustering approaches for wireless network to provide quality of services. Also, Wireless Communication is one of the fastest developing and the most dynamic as well as innovative regions in the correspondence field. Coming to Wireless Communication. It is the technique of sending data from one place to another, without taking the help of any association like wires, links or any physical medium [3], [4], [6]. Mostly in the correspondence framework, data is transferred from transmitter to beneficiary which is put through a restricted separation. But with the help of Wireless Communication, the transmitter and recipient can be placed anywhere between scarcely any meters (like a T.V. Controller) to almost thousands of kilometres (Satellite Communication) [3], [7]. In the world of correspondence, wireless communication is an important aspect of our life. In our day to day life, the highly utilized Wireless Communication Systems are GPS, Mobile Phones, Bluetooth Audio,RC, Wi-Fi and goes on. Thus combining optimization and wireless communication i.e. optimized wireless communication will play a key and important role for us today and in future [8]. Thus, this paper emphasis on re-viewing the optimization algorithms, majorly Differential Evolution, its modification and the application of the same in various different fields including wireless communication (multiple access techniques). More than 100 research papers have been ransacked, but some of the most important papers have been discussed in this paper.

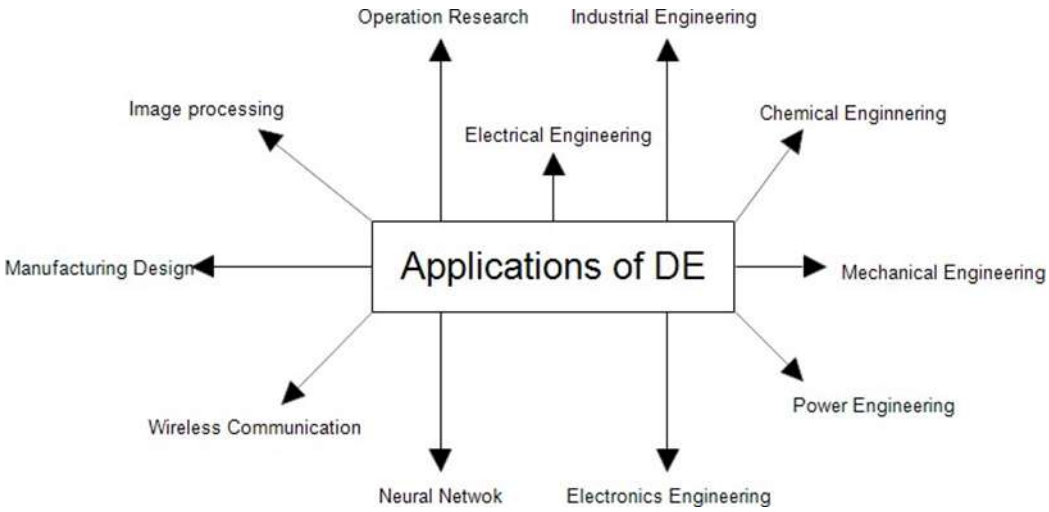

FIGURE 1 :DE APPLICATIONS

II. Literature Survey

Fig 1 and Fig 2 shows the different applications of DE and different variants of DE. Based on different applications and different variants, some important literature re- views are explained in the following.

Fig 2: Different DE variants proportion

Differential evolution algorithm (DEA) is a stochastic, population-based optimization method. In this study, the authors suggest new scheme for each alteration and Crossover operators with a purpose to make better performances of the usual DEA. The benefit of those proposed operators is that they're “parameters-less”, and not use a tuning part of algorithm parameters that is usually a drawback of DEA. As soon as the modified differential evolution is presented, a big comparative evaluation is carried out with the aim to evaluate each correctness and effectivity of the proposed operators. Benefits of proposed DEA are utilized in a very important process of recent structural engineering that's mechanical identification below outside dynamic loads. That is as a result of the significance of utilizing a “parameterless” algorithm in identification issues whose traits sometimes differ strongly case by case, needing a without stopping arrange of the algorithm proposed. This vital benefit of proposed optimizers, in entrance of different identification algorithms, is used to develop a computer code appropriate for the automated identification of an easy supported beam topic to an influence load, that has been examined each utilizing numerical simulations and actual normal assessments dynamic. The outcomes indicate that this algorithm is a riveting candidate for traditional functions in structural identification issues [9].

Selection operation performs an important function in differential evolution (DE) algorithm. A brand new DE algorithm primarily based on a better selection operation is introduced in this study. It was observed that there was neither a sensible technique to keep up the distribution of population nor a correction to the variables out of bounds in mutation operation in a basic differential evolution algorithm. The quick non-dominated sorting method and the spatial distance algorithm which had been utilized to the start of the selection method, in addition to a technique to repair the transboundary variables within the mutation section, have been adopted to optimize the DE algorithm. The reformative algorithm might acquire uniformly distributed and efficient Pareto-optimal units when utilized to the classical multi-objective take a look at functions; it carried out outstandingly within the experiment of optimizing the quality, the time and the cost in a project in comparison with the earlier work [10].

The purpose of this examination was to estimate the brittleness of intact rock by making use of the differential evolution (DE) algorithm after which to check the outcomes obtained from the optimum hypothesis with literature. For this aim, a number of models together with linear and nonlinear had been developed for predicting the brittleness via DE algorithm utilizing the data set obtained from 48 tunnel instances across the world. Every model has been developed utilizing 80% of the data set as training and 20% of the data set as testing at random. After that, developed models are compared according to the computer process unit (CPU), coefficient of correlations (r^2), a number of function evaluation (NFE) and mean-squared error (MSE) values to determine the accurate one among them. It's discovered that the values r^2,NFE, MSE and CPU ranged between 0.9385–0.9501,7217–11,176 8.2616–9.938 and 4.91–36.22, respectively, with the quadratic technique (QT) indicating one of the best performances. It's concluded that the DE algorithm is itself a very highly effective technique for calculating the brittleness; however, the QT is superior for the most part for simulations wherein optimization and computational time is critical [11].

This study displays a passive target localization issue in Wireless Sensor Networks (WSNs) utilizing the noisy time of arrival (TOA) measurements, obtained from the single transmitter and a number of receivers. The objective function is calculated under the Gaussian noise consideration as a maximum likelihood (ML) estimation issue. Accordingly, the objective function of the ML estimator is a highly nonlinear and non-convex function where conventional optimization strategies usually are not appropriate for this sort of problem. Hence, a modified algorithm primarily based on the hybridization of adaptive differential evolution (ADE) and Nelder-Mead (NM) algorithms, named HADENM, is projected to search out the estimated place of the passive target. In this study, during the process of evolution, the control parameters of the adaptive differential evolution algorithm are updated adaptively. Also, an adaptive adjustment parameter is configured to offer a balanced proportion between the exploration and exploitation abilities. Moreover, the exploitation is reinforced utilizing the NM technique by modifying the accuracy of the best solution finding from the ADE algorithm. Statistical evaluation has been done, to evaluate the advantages of the proposed modifications on the optimization performance of the HADENM algorithm. The comparability outcomes show that the modifications proposed in this study can enhance the general optimization performance. Furthermore, the simulation reveals that the proposed HADENM algorithm can attain the Cramer-Rao lower bound (CRLB) and execute the differential evolution (DE) algorithms and constrained weighted least squares (CWLS). The obtained outcomes show the high accuracy androbustness of the modified algorithm for fixing the passive target localization issue for a wide range of measurement noise levels [12].

This paper projected a modified version of the evolutionary algorithm called hybrid evolutionary algorithm consisting of guided local exploration and set based DE differential evolution algorithm for automated process discovery. The major innovations in this study are, firstly the hybrid evolutionary method is projected for rapid approximation of optimal solution along with to search the solution space after that to skip the local optimum a particular local exploration technique is added. Two new operators of differential evolution are presented secondly, with the help of this crossover and mutation are performed efficiently on the casual matrix. Thirdly efficiency of the algorithms is improved by a fine-grained evolution process, in which local exploration is guided to improve the efficiency. Experiments were executed on 22 artificial event logs including 68 different event logs, two real event logs and 44 noisy event logs. Not only that, the modified algorithm was compared with three different well-known algorithms of process discovery. Experimental outcomes display that the novel algorithm can achieve better performance along with faster converge speed [13].

In this paper, the diagnostic system follows a general model-based architecture where the correlation coefficient of the output signal is used to detect inconsistencies between model predictions and sensor data. A defect detection system and a defect identification system are designed. In the fault identification system, a model with variable parameters is used to simulate the real system. The output correlation coefficient between the fault detection system and the fault identification system is formulated as an optimization problem. It is solved by evolutionary algorithms for estimating fault parameters. By integrated estimation of all system parameters, the coordinates of the fault point in the parameter space can be obtained and the severity of the fault and the mode of the fault (single fault or multiple faults) can be determined. Compared with common residual-based methods, e.g., filter and adaptive observer methods, the proposed method reduces the number and complexity of the observer for high-dimensional parameter estimation. It overcomes the problem of combinatorial explosion of fault modes and simplifies the fault diagnosis structure. To our knowledge, there are few papers on an adaptive isolation and identification mechanism that combines observers and intelligent optimization algorithms. Using the great international search ability of an evolutionary algorithm, the planned method is additional advantageous to conquer narrow optimality compared with the usual adaptive search mechanism based on parameter incline change [14].

The authorof this paper used Alamouti's space time code for the multicarrier CDMA system. In this study genetic algorithm is used to calculate receiver weights having two variations for the MC-CDMA system. The receiver complexity is reduced by the proposed technique. Convergence rate and bit error rate are modified by enhancing the chromosomes and genes of the GA in both the techniques as compared with the conventional receiver (LMS based) of multicarrier code division multiple access techniques. The outcomes are verified by simulation [15].

In this paper chaotic (logistic map) based DE algorithm is proposed for the hydroelectric system to maximize the generation benefit per day. The authors used the stochastic logistic map, symmetry and ergodicity property to enhance DE for the proposed power-generation approach. The outcomes of the experiment show that the robustness and effectiveness of the proposed chaotic differential evolution algorithm are better than other techniques which are existed [16].

In this paper, DE algorithm based UAV (unmanned aerial vehicle) is studied. Four different tuning parameters are there in the DE algorithm, namely, generation number, crossover, differential weight and population size. According to different applications, these tuning parameters' optimum settings are varied. This study represents an optimization technique of the DE algorithm for tuning the parameters of path planning of UAVs. Improvement of output path and reduction of the computational cost of UAV is achieved by using the proposed optimizes DE algorithm [17].

The study is based on SDMA (Space Division Multiple Access) by using optimum MUD (multi-user detector) with the help of a genetic algorithm. Basically, the communication system is orthogonal frequency division multiplexing (OFDM). The convergence time is reduced in the proposed technique by reducing the search space of genetic algorithms by the authors. Overloaded scenario problems are investigated with the help of a modified technique by the authors. But computational complexity was compromised in this study to get better performance [18].

The authors in this paper merge different chaotic maps with differential evolution having self-adaptive nature in the application of image thresholding. The objective function used by the authors is Kapur entropy which maximizes the entropy of the different regions in the image. Three chaotic maps are the Logistic, Kent and Tentare used by the authors in this paper. The proposed chaotic maps based on DE are compared to the original DE self-adaptive DE and the state-of-the-art algorithms tested on four different images. The outcomes show that the proposed method gives better results than other algorithms [19].

In this paper, author presented chaotic spreading sequences based Low Rate Wireless Personal Area Network which enhances the performance. Sample-based chaotic signals is generated by varying 1D (dimensional) chaotic map system parameters. Optimized chaotic sequence is generated by using analysis of correlation properties. The authors used in this paper a high value of Golay figure of merit for optimized spreading code which gives better bit error rate and better synchronization performance. The optimized chaotic code is compared with Gold Code and it outperforms the Gold code performance [20].

The author of this paper proposed an efficient PARP (peak to average power ratio) reduction technique for (MCCDMA) multi-carrier code division multiple access downlink system. Both fully loaded and lightly loaded models are considered when using the orthogonal sets of Golay complementary sequences and Walsh Hadamard sequences. The proposed model needs slight improvement to base station of MCCDMA and mobile terminals negligible complexity [21].

In this paper narrowband jammer deletion is developed as an optimization problem. Computational intelligence methods are used to calculate the optimal weight. The author compared the complexity, error rate performance and implementation problems of different computational intelligence methods like Genetic Algorithm, Particle Swarm Optimization (PSO) and Least Mean Square (LMS). Narrow Band Interference can be suppressed with these newly generated techniques, which is experimentally proved by the authors using BER (Bit error rate). The proposed tuned parameters PSO algorithm outperforms the other algorithms along withdifferent schemes of PSO [22].

Storn and Price in this paper suggested the appropriate value of Cr, NP and F. The authors suggested that the value of NP should lie between 5D and 10D, Dis the dimension of the problem. And scaling factor F, like 0.5. Crossover rate a range from 0.4 to 1 as suggested by the authors. According to the authors, less number of parameters are changed for a small value of Cr and vice versa because in the selection process more trial vectors are selected [23].

Considering D as a dimension, the authors of this paper suggested that NP should lie between 3D to 8D. By taking the scaling factor as 0.6, the mutation procedure scales the difference vector. The authors suggested taking the value of the crossover rate from 0.3 to 0.9. Rastrigin, Rosenbrock and Sphere, with help of these benchmark functions, parameter settings are calculated. The outcomes display that searching capability and converging speed is more for the algorithm for these parameter settings [24].

The appropriate values for Cr, NP and F are experimentally analyzed in this paper. According to the author, F should have values between [0.4, 0.95] and havean initial value of F of 0.9. For separable functions value of Cr should be between 0 to 0.2 and (0.9, 1) for dependent parameter functions [25].

To solve optimization problems accurate value of the control parameter is very important and which is explained by this paper. It demonstrates that for a larger value of NP there is a lower risk of stagnation. The number of trial solutions will reduce for choosing scaling factor value is 1, hence it is not recommended by the authors. A crossover rate having a value of 1 is also not recommended for a number of effective trial solutions. But the value 0.99 is recommended for both crossover rate and scaling factor but not 1 [26].

These two papers tell that to solve optimization problems, how important it is to select the appropriate values of the control parameter is. Wrong selection of parameters can lead to the in-activeness of the algorithm, which is clearly described by these papers with the help of an experiment. For differential evolution, proper selection of control parameters is very essential. Therefore, to find the best values, the control parameter's self-adaptation process is necessary [23-24].

In this study a fuzzy adaptive differential evolution is projected which is known as FDE. The error between the global minimum and the actual value of a function can be minimized by utilizing fuzzy logic. Fuzzy controllers are used here and input values arecombined with the relative value of functions and modified the individuals to adapt crossover rate and scaling factor. The outcomes display that the modified technique outperforms the basic differential evolution algorithm [27].

Here the creator proposed parameter adaptation primarily based on inhabitants diversity, Population diversity based parameter adaptation technique is proposed in this paper by the authors. The thought of this study is to assemble the parameters adaptive in order to try not to the fast lower of population variance and in [38] authors planed an adaptive Pareto DE technique for multi-objective optimization and the projected APDE's is evaluated and measured with the help of island model-based parallelization and Pareto front approximation [28].

In this study, multi-objective problems are solved by using a proposed self-adaptive crossover rate. Every individual encoded the crossover rate value simultaneously to evolve with another individual. Gaussian distribution N (0, 1) is used to generate the scaling factor for each individual. The optimization solution in this paper is found for the scaling factor value greater than 1 [29-30].

SDE (self-adaptive differential evolution) is explained by this paper. In this paper self,the adaptive parameter is the scaling factor and normal distribution N (0.5, 0.15) is taken for the crossover rate. The projected algorithm displays better outcomes compared with other variants of DE [31].

This paper projected two self adaptive parameters, one is NP and another one is population size. The work done by the author here is on the basis of [30]. The projected work is known as DESAP. The findings of the projected work are compared with a differential evolution algorithm with a static population. Optimization of the absolute encoding technique shows better results than a relative encoding technique for self-adaptive NP, which is clearly observed in this paper. Also, various benchmark functions are used by the authors to validate the algorithm [32].

Computational effort and effect of NP for solution considering differential evolution both are experimentally tested in this paper with the help of benchmark functions. The result of NP by taking 10D and 30D are presented for two mutation schemes. The projected work also displays the interaction between mutation schemes, population size and dimensionality [33].

The self-adaptive differential algorithm is projected in this paper, here superior solutions are generated by learning from past experiences. Parallel populations are ensemble here. No function evaluations for each population describe the self adaptive property. 14 constrained optimization problems are utilized to test the proposed work and the outcomes are compared with differential evolution by taking the single value of NP [34].

In this work scaling factor's value varied from 0.5 to 1 randomly for each vector. Again in [31], a different value of a scaling factor is taken for each vector. DETVSF, which is a time-varying scale factor scheme, is also explained in this paper where the value of F decreases from 1 to 0.5 linearly. This decrease in scaling factor helps in exploration and exploitation [35].

OBL concept is introduced by the authors of this paper with differential evolution. To generate the opposite vector as there is no limitation, OBL fitted with DE. For different dimensions, the proposed work performances are displayed. Also, the acceleration rate is compared with various dimension sizes. With the help of the opposition-based technique and random initialization technique, the outcomes are compared [36].

This paper discusses the work of the DE algorithm and OBL when both are integrated. The author considered the noise-free environment for initialization of population and generation jumping process is applied. The Fittest individuals and opposite population for the next generation are calculated by Jr (predetermined probability) which are selected from the current population and opposite population rather than the new population generated from each iteration [37].

In this study, initial population generation is integrated with the versatility of OBL which can develop and discover noisy problem based searched places. Nosy function (σ = 0.75, 0.50, 0.25, 0) based DE is implemented in this work [38].

This paper displays the generation of three different types of jumping trends known as self-adaptive, adaptive and deterministic. According to the time for each vector, jumping trends can be changed to jump to the opposite direction [39].

An extended ODE is projected in this paper, where quasi that is the middle point is found in between the primary point and its opposite point of the newly generated solution candidate. By updating the boundaries from opposite points and quasi, the search space can be narrowed down, which is clearly shown in the proposed work. [40].

This paper displays a modified DE (micro-ODE)with application in image thresholding. Normalized grey level images and binary images are compared to find out the difference between threshold images from various techniques and the original image of grayscale by using micro ODE and Micro DE through pixel to pixel technique [41].

The extension of [37] is presented in this paper. The work displays here explore [37] with respect to population size, dimensionality, jumping rate and mutation operators. Not only those various variants of DE are also compared in this paper [42].

In this discussion,the optimization process is enhanced by modifying mutation by incorporation free mind searching sense of animals with mutation. To apply the idea, randomly choose the initial population on the supposition of worst in initial and opposite marked location. Outcomes show that the projected work has performance limitations in presence of interference and the number of iterations is also fixed [43].

High dimensional problems are being solved in this paper using GODE (global OBL). If the generated values are satisfactory, depending upon the generated opponent, GODE executes with random otherwise basic DE is executed. The projected work is validated on different high dimensional issues by taking D values as1000, 500, 200, 100 and 50 [44].

In this study, using DE and ODE, Generation Expansion Planning Problem (GEP) is solved. To modify the basic GEP, Virtual Mapping Procedure (VMP) and GEP are integrated. VMP is presented in Generation Expansion Planning issues (GEP) to change the aggregation of candidate units in dummy decision variables by integrating ODE. The comparison of the projected work and dynamic programming technique is also displayed [45].

The authors in this paper proposed a modified mutation and also a modified crossover action with two new variants, both of which are focused on exploration and exploitation. In each generation sorted population is utilized. There are two sets of vectors, one set contains the best vectors and the remaining are in another set. For the first proposed variant of mutation, the base vector is selected from the first set of vectorswhich contains the best populations and from the other set of vectors other two are selected for difference calculation. Modified crossover operation is carried on if the donor vector is more suitable than the target vector otherwise target and trial will be the same. In the second proposed variant, the other set members are utilized for new mutation and the remaining technique is the same as the first variant. In this variant, the base vector and the difference vector's left terminal are chosen from the first set of vectors and the third vector from another set [46].

This paper projected a balanced exploration and exploitation strategy for mutation operation. The population is partitioned into three parts on the basis of fitness. Individuals indexing is executed such as fitness will be better for lower index value, and the individual belongs to first class. In the second class, medium performers are there and the worse vectors are there in the third class with a higher index [47].

41. In this work the author utilized a crossover activity which gives better trials because of its rationally invariant property. The authors advised that the function landscape may be made pseudo separable by rotating the co-ordinating entity earlier than the crossover operation. On this technique, the crossover could be carried out and on the other hand, it might probably be rotated again to the unique position. To achieve such a co-ordinate system, eigenvectors of covariance of the population could be used as a rotation matrix. By multiplying the matrix of eigenvectors with them, the rotation of target and donor is finished. Crossover is performed in these rotated vectors. Then afterwards the technology of trials, they've introduced again to the unique place by multiplying them with the conjugate transpose of the rotation matrix. The proposed concept is computationally expensive for large scale issues [48].

In this study,the authors explain two modified DE and after comparing both, the wavelet-based DE is applied in the DSSS system. An experimental result shows that the proposed scheme can be applied to wireless communication systems [49].All paragraphs must be indented. All paragraphs must be justified, i.e. both left-justified and right-justified.

III. Conclusion

The present study has been concluded in two phases. individual of these two phases present the survey of literature on the basic aspect of DE for different applications and the other phase provide the different alteration of DE. Both phases will help in identify the potential areas of research that can be done in DE. DE is a natural fit for constant optimization problems and some hard work are required to make it friendly and practical for discrete combinatorial optimization problems. Many suchworks are being carried out in the field of research to develop a appropriate discrete variant of DE. Also, it has been observed that the application of DE to solve multi-objective optimization problems is restricted.

IV. Future Directions

These two research areas which are explain in this paper should be explore additional to realize the possible of DE. Finally, the authors would like to include that even though they have try to include the mainly relevant DE publications, it is possible that some important articles might have been missed, for which the authors express regret.

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