

# Differential Evolution Algorithm: Application in Optimization to Engineering Problems

Prashant A Giri<sup>#1</sup>, Bhargavi A Ketkar<sup>#2</sup>, Charvee M Gurav<sup>#3</sup>,  
Sahil P Patil<sup>#4</sup>

<sup>#</sup>Department of Chemical Engineering,  
Finolex Academy of Management and Technology, Ratnagiri, India, 415639

Date of Submission: 01-12-2022

Date of Acceptance: 10-12-2022

**ABSTRACT** — Differential Evolution (DE) is optimization technique inspired by nature based non-conventional evolution. DE's exceptional accuracy at numerical optimization, faster convergence & its independence on initial and final constraints defines its value for providing an excellent solution set. The DE algorithm includes four stages - generation, mutation, crossover and population. It provides solutions for a wide set of optimization problems with equality or inequality constraints regardless of stability and dimension of problem.

This work systematically implemented DE Algorithm for solving two benchmark problems from literature and frequently used by researchers in this field. The solution by DE and conventional method have been compared to check the effectiveness of DE. It is found that DE is simple to implement and converges faster towards global optima than other methods.

**Keywords** — Optimization, Differential Evolution, Genetic Algorithms, Evolutionary Algorithms

## I. INTRODUCTION

Optimization plays a very important role in the design, planning and operation of chemical processes. Optimization refers to finding one or more feasible solutions, which corresponds to extreme values of one or more objectives. Optimization is a wide area of research, which prescribes a particular method for solving a particular class of problems like Linear Programming Problems (LPP), Integer Programming Problems (IPP), Quadratic Programming Problem (QPP), Non-convex optimization and many more [36]. The difficulty, however, arises when it becomes difficult to identify the nature of the problem. The need for

finding such optimal solutions in a problem comes mostly from the extreme purpose of either designing a solution for minimum possible cost of fabrication, or for maximum possible reliability, or others [1]. Because of such extreme properties of optimal solutions, optimization methods are of great importance in practice, particularly in engineering design, scientific experiment and business decision making. More recently, a new evolutionary computation technique, called differential evolution (DE) algorithm, has been proposed and introduced [8-11,37,38]. Over the last decade, evolution algorithms have been extensively used in various problem domains and succeeded in effectively finding the near optimal solutions. Evolutionary optimization techniques have been used to solve chemical process optimization problems to overcome the limitations of classical optimization techniques. A wide variety of heuristic optimization techniques have been applied such as genetic algorithm (GA) [3, 4], simulated annealing (SA) [5], Tabu search [6], and particle swarm optimization (PSO) [7]. The results reported in the literature were promising and encouraging for further research in this direction. DE does not require the optimization problem to be differentiable, as is required by classic optimization methods such as gradient descent and quasi-newton methods. DE can therefore also be used on optimization problems that are not even continuous, are noisy, change over time, etc [2].

In 1995, Price and Storn [37] proposed a new floating point encoded evolutionary algorithm for global optimization and named it Differential Evolution owing to a special kind of differential operator, which they invoked to create new offspring from parent chromosomes instead of classical crossover or mutation. The algorithm is

inspired by biological and sociological motivations and can take care of optimality on rough, discontinuous and multi-modal surfaces. The DE has three main advantages: it can find near optimal solutions regardless of the initial parameter values, its convergence is fast and it uses few number of control parameters. In addition, DE is simple in coding, easy to use and it can handle integer and discrete optimization [8-11]. Differential evolution (DE) is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality [2].

Originally, Price and Storn [37] proposed a single strategy for differential evolution, which they later extended to ten different strategies. The performance of the DE algorithm was compared to that of different heuristic techniques. It is found that the convergence speed of DE is significantly better than that of GA [5, 6]. The performance of DE was compared to PSO and evolutionary algorithms (EA's). The comparison was performed on a suite of 34 widely used benchmark problems. It was found that DE is the best performing algorithm as it finds the lowest fitness value for most of the problems considered in that study. In addition, DE is robust; it is able to reproduce the same results consistently over many trials, whereas the performance of PSO is far more dependent on the randomized initialization of the individuals [38]. In addition, the DE algorithm has been used to solve high-dimensional function optimization (up to 1000 dimensions) [13]. It is found that it has superior performance on a set of widely used benchmark functions. Therefore, the DE algorithm seems to be a promising approach for engineering optimization problems. It has successfully been applied and studied to many artificial and real optimization problems [14-18].

Keller et al [19] applied DE algorithm to find the minimum total annualized cost of the non-equilibrium reactive distillation for the synthesis of ethylene glycol, which is a MINLP optimization problem. Artificial Feed-forward Neural Networks (FNN's) have been widely used in many application areas in recent years and have shown their strength in solving hard problems in Artificial Intelligence [33]. Another application was within the Design of Public Lighting Installations Maximizing Energy Efficiency. The algorithm was used to calculate the most energy efficient solution for luminaire spacing in addition to meeting the uniformity criterion [34]. This paper result shows that the optimized objective function values are better than those reported literature value and DE strategy (DE/best/1/bin) is a capable of providing optimized solutions, which are close to the global

optimum and reveals its adequacy for the optimization [20] have been widely applied DE algorithm on unmanned aerial vehicle (UAV) path planning. The improved version of DE, Improved-DE (IDE) has been introduced in different possible ways. One such paper shows results like using the IDE algorithm to solve all roots of high-order algebraic equations with real complex coefficients, some classic equations and nonlinear systems of equations with multiple solutions are tested. The experimental results clearly show that the solutions of all equations and nonlinear systems of equations can be found completely [35]. Another, modified version DE was used by Koutny (2016) proposed Meta-DE in the medical field. They validated their results in measuring the continuous blood glucose level in diabetic patients from Jaeb Center for Health Research [36].

Additionally, the results are compared to those reported in the literature and with other conventional and non-conventional techniques.

## II. DIFFERENTIAL EVOLUTION ALGORITHM

Differential Evolution (DE) is one of the well-established population-based evolutionary algorithms, which was first introduced by Storn and Price for solving the Chebyshev polynomial fitting problems. DE is capable of handling nonlinear, linear, and multimodal objective functions and solving directional preferences over existing relays in the power system. The DE has also worked to train the weight of the neural network to deal with real-world problems. The basic idea of this technique is to avoid repetition of the existing set of solutions. Classic DE has two main control parameters and that need to be settled efficiently. The settlement of these parameters including the scaling factor, and the probability of crossover. Crossover is the main source of exploration, the mutation is utilized for exploitation purposes, and selection operators bring down the pressure for the survival of fittest individuals to evolve the population. The adjustment of various parameters used in search operator implementation is mainly problem-dependent, and their proper settings are quite difficult and time-consuming while performing trial and error experiments [2].

Different search operators behave differently at different levels of the optimization search process while dealing with complicated optimization and search problems. It is quite difficult to determine that this particular crossover or mutation or selection operator is useful in this particular proposition optimization process.

The optimization method is divided into the traditional optimization methods and heuristic optimization methods. The traditional optimization methods mainly realize the order of single feasible solution and deterministic search based on the objective function gradient (or derivative) information. And the heuristic optimization methods are a kind of bionic algorithm, which realizes the parallel and stochastic optimization of multi solutions by using the heuristic strategy. The heuristic search algorithms do not require the continuous and differentiable information of the objective function, and take on better global search ability [23, 24]. In recent years, evolutionary algorithm have been applied to the solution of non-convex problem in many engineering application such as optimal design of an auto thermal ammonia synthesis reactor, which presents the effective use of DE to optimize the systems objective function subject to a number of equality constraints involving solution of coupled differential equations [25, 26]. The global optimization of MINLP problems is an active research area in many engineering fields. In this work, DE is used for the optimization of non-convex MINLP problems and a comparison is made among the algorithms based on hybrid of simplex and simulated annealing (M-SIMPASA), GA, and DE. It is found that DE is significantly faster and yields the global optimum for a wide range of the key parameters. Results indicate that DE is more reliable, efficient, and hence a better approach to the optimization of nonconvex, nonlinear problems. DE is found to be the best evolutionary computation method in all the problems studied. [27]. The differential evolution approach is presented for multi-objective optimization problems in optimization of adiabatic styrene reactors. The proposed algorithm is applied to determine the optimal operating condition for the manufacture of styrene [28]. In case of optimal design of a gas transmission network, an evolutionary computation technique has been successfully applied for the optimal design of gas transmission network. The proposed strategy takes less computational time to converge when compared to the existing technique without compromising with the accuracy of the parameter estimates [15]. The first successful application of DE has been presented by Babu and Munawar for the optimal design of shell and tube heat exchanger [29].

Differential evolution (DE) is a generic name for a group of algorithms that are based on the principle of Genetic Algorithm (GA) but have some inherent advantages over genetic algorithm. DE is an adaptive algorithm which falls under the

category of evolutionary algorithms. Differential evolution algorithms are very robust and efficient in that they are able to find the global optimum of a function with ease and accuracy [23]. Differential evolution algorithms are faster than genetic algorithms. In other words, genetic algorithms evaluate vectors suitability. In differential evolution, this vector's suitability depends on whether the problem is a minimization or a maximization problem. In differential evolution, no coding is involved and floating-point numbers are directly used [24, 25].

Differential evolution (DE) is one of the well-established population-based evolutionary algorithms, which was first introduced by Storn and Price for solving the Chebyshev polynomial fitting problems. DE is capable of handling nonlinear, linear, and multimodal objective functions and solving directional preferences over existing relays in the power system. The DE has also worked to train the weight of the neural network to deal with real-world problems. The basic idea of this technique is to avoid repetition of the existing set of solutions. Classic DE has two main control parameters and that need to be settled efficiently. Crossover is the main source of exploration, the mutation is utilized for exploitation purposes, and selection operators bring down the pressure for the survival of fittest individuals to evolve the population. The adjustment of various parameters used in search operator implementation is mainly problem-dependent, and their proper settings are quite difficult and time-consuming while performing trial and error experiments.

Different search operators behave differently at different levels of the optimization search process while dealing with complicated optimization and search problems. It is quite difficult to determine that this particular crossover or mutation or selection operator is useful in this particular proposition optimization process.

Deciding the DE key parameters: Population size (NP) should be 5 to 10 times the dimension of the problem. The range of values of F is  $0 < F < 1.2$ , but the optimal range is  $0.4 < F < 1.0$ . Effectiveness of  $F < 0.4$  and  $F > 1.0$  is still studied. As a good first guess, Crossover Ratio (CR) can be chosen as 0.9 varying value on the other end could be 0.1. Judging by the speed of convergence, choose a value of CR between 0 and 1 [2].

### III. DE COMPUTATIONAL FLOW:

The main features of the DE algorithm can be stated as follows and represented in Fig. 1 [31].

Step 1- Population initialization: Initialize population randomly between the given upper and lower bounds for all the parameters.

Step 2-Cost Evaluation: calculate the objective function value for initial population.

Step 3-Mutation and Crossover

Take  $i$  as population counter  $i = (0, 1, 2, \dots, 19)$

a. Randomly choose 3 population points  $a$ ,  $b$ , and  $c$  such that  $i \neq a \neq b \neq c$

b. Select randomly a parameter  $j$  for mutation ( $j=0, 1$ )

c. Generate a random number  $[0,1]$

If random number  $< CR$ ,

Trial  $[j] = x_1 [c] [j] + F (x_1 [a_1] [j] - x_1 [b] [j])$

If random number  $> CR$ ,

Trial  $[j] = x_1 [i] [j]$

Check for bounds:

If bounds are violated, then randomly generate the parameter as shown below:

Trial  $[j] = \text{lower limit} + \text{rand.no.} [0, 1] (\text{upper limit} - \text{lower limit});$

Repeat Step 3 till all parameters are mutated.

Step4-Evaluation: Calculate the objective function value for the vector obtained after mutation and crossover.

Step5- Selection: Select the least cost vector for the next generation, if the problem is of minimization.

Step 6- Repeat: Repeat step 3 to 5 for a specified number of generations, or till some termination criterion is met.

### Figure 1: Flowchart for Differential Evolution Algorithm

## IV. CASE STUDIES

### OBJECTIVE:

The objective of the present work was aimed at finding the global optimum solution for given Mathematical problems by Evolutionary Algorithm like DE or Differential Evolution mentioned in (Kumbhojkar G. V., "Applied Mathematics-III", Chemical Engineering 2015-16.) DE carries the optimization and the results obtained are compared with other conventional and non-conventional techniques. The analytical solution of the differential evolution optimization problem involves a number of iterations and they are time consuming. The function values when solved by iterative conventional methods or analytically solved are compared with those found at the end of generation completion by DE. By this way, results obtained are then compared for better convergence, efficiency, faster speed, and usability.

### 4.1 Problem definitions:

#### Problem Statement 1

Maximize  $Z=3x_1+x_2+1$

Subject to  $0 \leq x_1 \leq 3, 0 \leq x_2 \leq 3$

(Answer by Conventional Method:  $x_1= 0.5, x_2= 1.3856$  and  $Z_{\max}=3.8856$ ) (Kumbhojkar G. V., "Applied Mathematics-III", Chemical Engineering 2015-16.)

#### Problem Statement 2

Minimize  $Z=(x_1 - 1.5)^2 - (x_2 - 4)^2$

Subject to  $4.5x_1+2x_2 \leq 36$

$x_1+x_2 \leq 14$

$x_1, x_2 \geq 0$

(Answer by Conventional Method:  $x_1= 1.92, x_2= 3.6500$  and  $Z_{\min}= 0.52$ ) (Kumbhojkar G. V., "Applied Mathematics-III", Chemical Engineering 2015-16.)

### Methodology:

By implementing the DE algorithm, we have solved this problem analytically. This is an optimization problem in which objective function along with the constraints are given.

1. First of all we have to choose DE key parameters i.e. NP, CR and F.
2. Randomly choosing value of  $x_1$  and  $x_2$  between the upper and lower bounds.
3. Third step is cost evaluation i.e. we have to put value of  $x_1$  and  $x_2$  in the objective function and calculate the cost.
4. To evolve individual 1 for the next generation the first member of the population is set as the target vector.
5. In order to generate the noisy random vector 3 individuals (2, 4, 6) from the population size are selected randomly. The weighted difference between individual 2 and individual 4 is added to the third randomly chosen vector individual 6.
6. Generate random number (0 to 1)

If random number  $> CR$  Target vector is used as Trial vector

If random number  $< CR$  Noisy random vector is used as Trial vector

- i. Trial vector compared with target vector and vector with lowest value of the two becomes individual 1 for next generation.
- ii. To evolve individual 2 for the next generation the second member of the population is set as target vector and the above processes are repeated.
- iii. This process is repeated NP times until the new population set array is filled which completes one generation.

## V. RESULT AND DISCUSSION

The performance of the differential evolution algorithm is tested by applying it to the above problems. The key parameters of DE-Crossover Ratio (CR), Number of population size (NP), Scaling Factor (F), and Number of iterations are varied over a wide range of their possible values. The above two optimization problems are solved by using differential evolution and conventional techniques and the results are obtained as shown in table 1 and table 2. The results obtained by differential evolution are compared with the conventional techniques; it is found that differential evolution is more suitable as compared to conventional techniques.

### Implementation:

The proposed DE algorithm is developed and implemented using the MATLAB software. Initially, several runs were done with different values of DE key parameters such as differentiation (or mutation) constant F, crossover constant CR, size of population NP, and maximum number of generations GEN which is used here as a stopping criterion. From the various strategies of DE, in this

paper DE/rand/1/bin has been used throughout. In this paper, the following values are selected as:

For problem statement 1: F = 0.8; CR = 0.5; NP = 20; GEN = 20

For problem statement 2: F = 0.8; CR = 0.5; NP = 20; GEN = 20

The results obtained by differential evolution are compared with the conventional techniques; it is found that differential evolution is more suitable as compared to conventional techniques.

### Implementation:

The proposed DE algorithm is developed and implemented using the MATLAB software. Initially, several runs were done with different values of DE key parameters such as differentiation (or mutation) constant F, crossover constant CR, size of population NP, and maximum number of generations GEN which is used here as a stopping criteria. In this paper, the following values are selected as:

**Solution for problem statement 1:** In this problem F = 0.8; CR = 0.5; NP = 20; GEN = 20. Problem statement 1 is minimization problem where answers by using DE the answers are 0.447 for  $x_1$ , 1.098 for  $x_2$  and value of function is 3.439.

**Table 1: Solution for Problem Statement-1**

GEN	$x_1$	$x_2$	f(x)	GEN	$x_1$	$x_2$	f(x)
Ind. 1	2.677	0.222	9.253	Ind. 11	2.295	2.354	10.239
Ind. 2	2.338	1.2524	9.2664	Ind. 12	2.032	2.322	9.418
Ind. 3	0.528	1.9536	4.5376	Ind. 13	2.689	2.206	11.273
Ind. 4	1.187	2.523	7.084	Ind. 14	2.020	2.4212	9.4812
Ind. 5	2.133	2.677	10.076	Ind. 15	2.404	2.039	10.251
Ind. 6	0.85	2.7028	6.2528	Ind. 16	2.023	2.2204	9.2894
Ind. 7	0.447	1.098	3.439	Ind. 17	2.000	2.1492	9.1492
Ind. 8	2.642	1.944	10.87	Ind. 18	2.093	2.681	9.96
Ind. 9	2.1456	0.662	8.0988	Ind. 19	2.076	2.810	10.038
Ind. 10	2.4314	2.1526	10.4465	Ind. 20	2.460	2.267	10.647

**Solution for problem statement 2:** In this problem F = 0.8; CR = 0.5; NP = 20; GEN = 20. Problem statement 2 is a maximization problem

where by using DE the answers are 1.6 for  $x_1$ , 3.5 for  $x_2$  and value of function is 0.26.

**Table 2: Solution for Problem Statement-2**

GEN	x <sub>1</sub>	x <sub>2</sub>	f(x)	GEN	x <sub>1</sub>	x <sub>2</sub>	f(x)
Ind. 1	0.2	1.1	10.1	Ind. 11	1.9	2.45	2.56
Ind. 2	0.3	2.2	4.68	Ind. 12	2.1	3.3	0.85
Ind. 3	0.04	0.3	15.82	Ind. 13	2.3	1.854	5.24
Ind. 4	0.5	2.5	3.25	Ind. 14	2.7	2.04	5.28
Ind. 5	0.6	2.9	2.02	Ind. 15	2.9	1.5	8.21
Ind. 6	0.7	2.05	4.44	Ind. 16	3.2	2.62	4.79
Ind. 7	0.8	2.7	2.18	Ind. 17	0.18	2.48	4.05
Ind. 8	1.2	2.54	2.22	Ind. 18	3.8	2.3	8.18
Ind. 9	1.4	2.2	3.25	Ind. 19	3.9	2.7	7.45
Ind. 10	1.6	3.5	0.26	Ind. 20	0.76	2.45	2.95

## VI. CONCLUSION

Differential Evolution algorithm has been proposed, developed and successfully implemented for engineering optimization problems. DE is naturally suited for continuous optimization problems and a certain level of effort is required for making it compatible for discrete and combinatorial optimization problems.

Due to simple structure, ease of use, speed and robustness, it has been shown that Differential Evolution is the more appropriate choice for optimization. Differential Evolution technique is much faster, has less computational burden when compared to non-traditional techniques and the estimation is much more accurate and efficient. The search for the global minimum is strongly dependent on the control parameters. Hence, differential evolution is a potential tool for accurate and faster optimization. On the basis of results of above solved problems, we conclude that differential evolution explores the decision space more efficiently than conventional and non-conventional techniques. Differential Evolution is more effective in obtaining better quality solutions.

## REFERENCES

- [1] Giri P. A., Apankar D. D., Gawas S. S., "Optimization of some chemical processes using Differential Evolution (DE) algorithm", International Journal of Creative Research Thoughts (IJCRT),(2018), Vol.6, pp. 736-740.
- [2] Giri. P.A., Gurav C.M., Ketkar B.A., Patil S.P., Apankar D.D., Gawas S.S., "Differential Evolution Algorithm: Application in Optimization of Chemical Processes", International Journal of Advanced Trends in Computer Applications, Volume 8 Number 3, (2021),pp. 93-98.
- [3] Lai L. L., Ma J. T., Yokohoma R., M. Zhao, "Improved genetic algorithm for optimal power flow under both normal and contingent operation states", Electrical Power Energy System, 19, (1997), pp. 287-291.
- [4] Osman M. S., Abo-Sinna M. A., "A Solution to the Optimal Power Flow using Genetic Algorithm", Elsevier Inc., 2003.
- [5] Miranda V., Srinivasan D., Proenca L. M., "Evolutionary computation in power systems", Electrical Power Energy System, 20 (1998), pp. 89-98.
- [6] Abido M. A., "Optimal power flow using Tabu search algorithm", Electric Power Components & Systems, 30, (2002), pp. 469-483.
- [7] Abido M. A., "Optimal power flow using particle swarm optimization", International Journal of Electrical Power and Energy Systems, 24, (2002), pp. 563-571.
- [8] Storn R., Price K., "Differential evolution-a simple and efficient adaptive scheme for global optimization over continuous spaces", in: Technical Report TR-, ICSI, (1995).

- [9] Das S., Abraham A., Konar A., "Particle swarm optimization and differential evolution algorithms: technical analysis", Applications and Hybridization Perspectives, pp. 1-38.
- [10] Kariba D., Okdem S., "A simple and global optimization algorithm for engineering problems: differential evolution algorithm", Turkish Journal of Electronics and Engineering 12 (1) (2004).
- [11] Storn R., Price K., "Differential evolution, a simple and efficient heuristic strategy for global optimization over continuous spaces", Journal of Global Optimization 11 (1997), pp. 341–359.
- [12] Charvee M. Gurav, Bhargavi A. Ketkar, Sahil P. Patil, Prashant A. Giri, "Application of the Differential Evolution (DE) Algorithm to Solve Engineering Optimization Problems", International Journal of Creative Research Thoughts (IJCRT), (2022), Vol.10, Issue 4, pp.55-59.
- [13] Zhenyu Yang, Ke Tang, Xin Yao, "Differential evolution for high-dimensional function optimization", IEEE Congress on Evolutionary Computation (CEC 2007) (2007), pp. 3523–3530.
- [14] J. Lampinen, "A Bibliography of Differential Evolution Algorithm", Springer, 2007.
- [15] Babu B. V., Chakole P. G., Mubeen J. H. S., "Differential Evolution Strategy for Optimal Design of Gas Transmission Network", Multidiscipline Modeling in Materials and Structures 1 (4), 2005, pp. 315-328.
- [16] Storn R., "Differential evolution design of an IIR-filter with requirements of magnitude and group delay", in: Proceedings of the IEEE Conference on Evolutionary Computation, 1996, pp. 268–273.
- [17] Storn R., "System design by constraint adaptation and differential evolution", IEEE Transactions on Evolutionary Computation 3 (1) (1999), pp. 22–34.
- [18] Daniela Z., "A comparative analysis of crossover variants in differential evolution", in: Proceedings of the International Multi-conference on Computer Science and Information Technology, (2007), pp. 171–181.
- [19] Keller T., Dreisewerd B., Gorak A., "Reactive distillation for multiple reaction systems: optimization study using an evolutionary algorithm", Chemical and process engineering 2013, 34(1), pp. 17-38.
- [20] Kai Yit Kok, Rajendra P., "Differential Evolution control parameter optimization for unmanned aerial vehicle path planning", (2016).
- [21] Das S., Abraham A., Konar A., "Particle swarm optimization and DE algorithm: Technical analysis, applications and hybridization perspectives", Advances of computational intelligence in industrial system, Springer Publication, pp. 1-38.
- [22] Price, K. and Storn, R., "Differential evolution", Dr. Dobb.s Journal, (1997), pp 18-24.
- [23] Angira, R. and Babu, B.V. (2003). "Evolutionary computation for global optimization of non-linear chemical engineering processes." Proceedings of International Symposium on process system engineering and control (ISPSEC 03), Paper No. FMA2, pp. 87-91.
- [24] Angira, R., and Babu, B.V., (2005) "Optimization of non-linear chemical processes using modified differential evolution (MDE)." In Proceedings of the 2<sup>nd</sup> Indian International Conference on Artificial Intelligence (IICAI-2005), 2005(pp. 911–923).
- [25] Angira, R., and Babu, B. V., (2006) "Optimization of process synthesis and design problems: A modified differential evolution approach." Chemical Engineering Science, vol. 61, pp.4707–4721.
- [26] Babu B. V., Angira R. and Nilekar A. "Optimal design of auto thermal ammonia synthesis reactor using differential evolution." Computers and Chemical Engineering 29 (5), 2005 pp. 1041-1045.
- [27] Babu B. V. and Angira R. "Optimization of thermal cracking operation using differential evolution." Proceeding of International Symposium and 54<sup>th</sup> Annual Session of IICChE (CHEMCON-2001), 2001.
- [28] Babu B. V., Chakole P. G., Syed Mubeen J. H. "Multi-objective differential evolution for optimization of adiabatic styrene reactor." Chemical Engineering Science 60 (17), 2005 pp. 4822-4837.
- [29] Babu, B. V. and Munawar, S. A. "Optimal Design of Shell & Tube Heat Exchanger by Different strategies of Differential Evolution." PreJournal.com - The Faculty Lounge, Article No. 003873, March 03 (2001), pp. 3720-3739.
- [30] Babu B. V., Chaturvedi G. "Evolutionary computation strategy for optimization of an

- alkylation reaction.” IChE (CHEMCON-2000), PP. 18-21.
- [31] Babu B. V., “Process Plant Simulation”, Oxford University Press, 2004.
- [32] Datta Suman, “Optimization in Chemical Engineering”, Cambridge University press 2016.
- [33] V.P. Plagianakos D.K. Tasoulis and M.N. Vrahatis,” A Review of Major Application Areas of Differential Evolution”, Studies in Computational Intelligence, 2008
- [34] Ovidio Rabaza, Daniel Gómez-Lorente, Antonio M. Pozo & Francisco PérezOcón, “Application of a Differential Evolution Algorithm in the Design of Public Lighting Installations Maximizing Energy Efficiency”, 2019
- [35] Ning, G., Zhou, Y. Application of Improved Differential Evolution Algorithm in Solving Equations. Int J Comput Intell Syst 14, 199 (2021)
- [36] Bilal, Millie Pant , Hira Zaheer, Laura Garcia-Hernandez, Ajith Abraham , “Differential Evolution: A review of more than two decades of research”, Engineering Applications of Artificial Intelligence, 90 (2020)
- [37] Storn R. and Price K., “Differential Evolution- A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces”, Journal of Global Optimization, Kluwer Academic Publishers, 11 (1997), pp. 341-359.
- [38] Vesterstrøm J., Thomsen R., “A comparative study of differential evolution, particle swarm optimization, and evolutionary algorithms on numerical benchmark problems”, IEEE Congress on Evolutionary Computation (2004), pp. 980–987.